Dynamic efficiency under uncertainty:
An empirical analysis for German dairy farms

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Greek letters and letter combinations

α	vector of drift parameters
β, ζ, ξ, ω	parameters to be estimated
γ	co-state variable
δ	depreciation rate
ε	error term
η	error term representing allocative efficiency
θ, υ	risk preferences
π	weighting factor
κ	time-specific effects
λ	allocative efficiency of variable factors
μ	allocative efficiency of net investment
ν	two-sided error term
ν_{σ^2}	error term representing production uncertainty
Σ	variance covariance matrix
σ	elements of the variance covariance matrix
τ	technical inefficiency
φ	technical efficiency computed by DEA
ψ	matrix in the Brownian motion
Ω	uncertainty of the state variable

Latin letters and letter combinations

a_0	constant term in the value function
A, M	second-order value function parameter
b	first-order value function parameter
c	quasi-fixed factor price
d^{edu}	dummy for agricultural education
d^{south}	dummy for regions in Germany
dv	Wiener increment
E_0	expectation operator
$F(\cdot)$, $f(\cdot)$	production function
$g(\cdot)$	production risk function
h	interest rate

I	gross investment
i	firm
j, j'	element of the vector of state variables
J	value function
J^a	value function in terms of optimized observables
J^b	shadow value function
K	quasi-fixed factor level
$\dot{K}$	net investment
$\dot{K}^*$	optimal net investment
$\dot{K}^{\mathrm{b}}$	shadow net investment demand
k	number of parameters for AIC and BIC
L	likelihood of the model
li	useful life of a dairy cow
ln	natural logarithm
$\overline{m}$	number of quasi-fixed factors
N	number of observations
$\overline{n}$	number of variable inputs
p^{cc}	price per culled cow
p^{dc}	price per dairy cow
$\overline{q}$	number of outputs
r	discount rate
t	time
u	one-sided error term
w	variable input price
w^b	shadow price for variable input
x	variable input level
x^*	optimal variable input level
x^b	shadow variable input level
y	output level
z	state variables

Other symbols

$\forall$	for all
∞	infinity
∂	partial derivative
$\sum$	sum

Acronyms and abbreviations

ACF	autocorrelation function
ADF	augmented Dickey-Fuller
AE	allocative efficiency
AI	allocative inefficiency
AIC	Akaike information criterion
AMI	Agrarmarkt Informations-Gesellschaft mbH (Agricultural Market Information Company)
AR(p)	autoregressive process of order p
AR	Argentina
ARCH	autoregressive conditional heteroscedasticity
BIC	Schwarz's Bayesian information criterion
BMEL	Bundesministerium für Ernährung und Landwirtschaft (Federal Ministry of Food and Agriculture)
CAP	Common Agricultural Policy
cf.	confer
CL	Chile
DE	Germany
DEA	data envelopment analysis
DRV	Deutscher Raiffeisen Verband e.V.
EC	European Community
EE	economic efficiency
EEC	European Economic Community
e.g.	for example
ES	Spain
et al.	et alii
EU	European Union
Eurostat	Statistical office of the EU
FADN	farm accountancy data network
GARCH	generalized autoregressive conditional heteroscedasticity
HJB	Hamilton-Jacobi-Bellman
HU	Hungary
IT	Italy
kg	kilogram
MA(q)	moving average model of order q
max	maximum
min	minimum
NL	Netherlands

PACF	partial autocorrelation function
PT	Portugal
R^2	coefficient of determination
SE	Sweden
SFA	stochastic frontier analysis
StoNED	stochastic non-parametric envelopment of data
TE	technical efficiency
TI	technical inefficiency
U.S.	United States of America
UY	Uruguay
w.r.t.	with respect to
ZMP	Zentrale Markt- und Preisberichtstelle für Erzeugnisse der Land-, Forst- und Ernährungswirtschaft GmbH

Acronyms of the West German federal states

BW	Baden-Württemberg
BY	Bavaria
HE	Hesse
NI	Lower Saxony
NW	North Rhine-Westphalia
RP	Rhineland-Palatinate
SL	Saarland
SH	Schleswig-Holstein

Summary

Dairy farming, the most important farming sector in the European Union (EU), has been subject to considerable de-regulation since the 2005 EU Common Agricultural Policy came into effect. Since the EU dairy sector was highly subsidized and subject to both price protection and production quotas, it is not surprising that the de-regulation led to increased commodity price volatility. Particularly for dairy farms, price volatility is a new challenge. Adjustment pressure, for example induced by increases in price volatility, is related to farm-level decision-making with regard to the optimal factor allocation in the long run. A vast body of literature relates technical and economic efficiency to dairy farm characteristics such as size, managerial ability or intensification of production. However, it is common for static approaches of efficiency—ignoring the role of time and the adjustment processes of farms with respect to the quasi-fixed factors—to be applied. This may result in biased frontier estimates and firms that actually behave optimally may appear inefficient.

The intertemporal linkages of production and (dis)investment decisions are emphasized by the concept of dynamic efficiency; however, until 2011 the literature on dynamic efficiency ignored uncertainty when deriving dynamic efficiency measures, even though uncertainty affects the optimal adjustment path and the optimal use of quasi-fixed factors. A dynamic efficiency model enhanced by Hüttel et al. (2011) addresses this gap. In contrast to existing models, this model incorporates factor price risk, and thus factor price volatility emerges as a variable in the theoretical factor demand equations, as well as in their empirical counterparts. This enables one to test whether disregarding price uncertainty will cause an omitted variable bias in the measurement of dynamic efficiency.

The contribution of this thesis is to analyze the dynamic efficiency of German dairy farms under uncertainty, which thus far has not been done. The application is conducted using German farm-level panel data with the aim of investigating whether West German dairy farms use net investment and variable factors in a technically and allocative efficient way in the long run. Moreover, the application will explore the role of uncertainty within the optimal factor allocation process. The results show that the analyzed German dairy farms operate at high levels of technical efficiency of net investment and variable factors: the average technical efficiency score of net investment is, on average, 0.959 and the technical efficiency score of variable inputs amounts to 0.948. Compared to technical efficiency, allocative efficiency is lower. The estimated values for allocative efficiency of net investment imply that all farms overuse their

dairy cow stock with regard to observed factor prices. In addition, the allocative efficiency of the variable factors (purchased feed) in relation to the numeraire factor (other inputs) indicates the suboptimal use of purchased feed.

With respect to the influence of uncertainty, the results state that the demand for feed is negatively related to the variance of the feed concentrate price and investment is negatively related to the variance of the milk price. Also scale matters: the results reveal a significant interaction between price uncertainty and livestock capital by size: uncertainty has a negative impact on farm-level investments in herd size that increases with farm size. The results further show empirical evidence for considering uncertainty when deriving (dynamic) efficiency measures: neglecting uncertainty within the estimation procedure will overestimate the average inefficiency score, and thus farms may appear inefficient. This finding is not only interesting for dairy farms; it also applies to other sectors that operate in highly-volatile markets.

Zusammenfassung

Der Milchsektor ist einer der bedeutendsten landwirtschaftlichen Sektoren in der Europäischen Union (EU). Seit die Reformen der Gemeinsamen Agrarpolitik 2005 in Kraft traten, wurde der Markt stark liberalisiert. Da der EU-Milchsektor bis dahin hoch subventioniert war und sowohl einer Preisabsicherung als auch Produktionsquoten unterlag, ist es nicht überraschend, dass die Liberalisierung zu erheblichen Preisschwankungen geführt hat. Besonders für Michvieh-betriebe stellt dies eine Herausforderung dar. Der Anpassungsdruck, zum Beispiel verursacht durch eine zunehmende Preisvolatilität, ist eng mit den betrieblichen Entscheidungsprozessen für die optimale langfristige Nutzung der Produktionsfaktoren verbunden. Ein weitreichender Teil der Literatur analysiert den Zusammenhang von Betriebsgröße, Betriebsführung oder Produktionsintensität mit technischer und ökonomischer Effizienz. Die statische Effizienzmessung ist hierbei weitverbreitet, vernachlässigt jedoch die zeitliche Abhängigkeit und die Anpassungsprozesse der quasi-fixen Faktoren, was zu verzerrten Ergebnissen in der ökonometrischen Schätzung führen kann. Betriebe, die eigentlich optimal wirtschaften, erscheinen ineffizient.

Die zeitliche Abhängigkeit von Produktions- und (Des-)Investitionsentscheidungen wird im Konzept der dynamischen Effizienzmessung aufgegriffen. Bis 2011 wurde jedoch bei der Herleitung dynamischer Effizienzmaße die Volatilität der Preise vernachlässigt, obwohl bekannt war, dass die Volatilität den Anpassungspfad und die optimale Nutzung von quasi-fixen Faktoren beeinflusst. Ein von Hüttel et al. (2011) erweiterter Ansatz greift diese Lücke auf. Im Gegensatz zu bestehenden Modellen berücksichtigt das Modell Faktorpreisunsicherheit, sodass die Faktorpreisvolatilität sowohl in den theoretischen als auch in den empirischen Faktornachfragegleichungen als erklärende Variable auftritt. Dies ermöglicht es zu untersuchen, ob die Messung der dynamischen Effizienz aufgrund ausgelassener Variablen verzerrt ist, wenn die Preisvolatilität vernachlässigt wird.

Der Beitrag dieser Dissertation ist es, die dynamische Effizienz deutscher Milchviehbetriebe erstmals unter Unsicherheit zu analysieren. Auf der Basis von Paneldaten wird untersucht, ob westdeutsche Milchviehbetriebe quasi-fixe und variable Produktionsfaktoren technisch und allokativ effizient einsetzen. Zudem wird die Rolle der Unsicherheit für den Prozess der optimalen Faktorzuteilung genauer beleuchtet. Die Ergebnisse zeigen, dass die untersuchten Milchviehbetriebe auf einem hohen technischen Effizienzniveau arbeiten. Die durchschnittliche technische Effizienz der Investitionen liegt bei 0,959, die technische Effizienz

der variablen Produktionsfaktoren bei 0,948. Im Vergleich zur technischen Effizienz ist die allokative Effizienz niedriger. Der Wert der allokativen Effizienz der Investitionen impliziert, dass die Milchviehbetriebe ihren Tierbestand bezüglich der Faktorpreise überbeanspruchen. Die allokative Effizienz der variablen Faktoren (Kraftfutter in Relation zu sonstigen Produktionsfaktoren) verdeutlicht, dass die Betriebe den Faktor Kraftfutter nicht optimal einsetzen.

Hinsichtlich der Bedeutung der Unsicherheit zeigen die Ergebnisse, dass die betriebliche Futternachfrage negativ mit der Futterpreisvolatilität verbunden ist und dass Investitionen negativ auf die Volatilität des Milchpreises reagieren. Auch hier spielt die Betriebsgröße eine Rolle. So ist eine signifikante Interaktion zwischen der Preisunsicherheit und der Herdengröße zu beobachten: Mit zunehmender Betriebsgröße nimmt der Einfluss der Unsicherheit auf die Investitionen zu. Die Ergebnisse belegen empirisch, dass die Preisunsicherheit bei der (dynamischen) Effizienzmessung von entscheidender Bedeutung ist: Wird die Unsicherheit vernachlässigt, führt dies zu niedrigeren Effizienzwerten und somit erscheinen die Betriebe ineffizient. Diese Ergebnisse sind nicht nur für Milchviehbetriebe relevant, sondern auch für Sektoren, die durch volatile Marktbedingungen gekennzeichnet sind.

1 Introduction

1.1 Motivation

As the most important farming sector in the European Union (EU), dairy farming has been subject to considerable policy changes, accompanied by increased milk and commodity price volatility. Particularly for dairy farms, price uncertainty is rather new compared to other sectors such as hog fattening, and can be assumed to further increase in the future (Keane and O'Connor 2009; Peerlings et al. 2010; Gorton et al. 2012). The 2003 Common Agricultural Policy (CAP) reform and the ensuing 2008 health check that decoupled direct payments from production levels, further reduced intervention prices, and stepwise increased milk quotas induced adjustment processes at the farm level. This was further enhanced by increasing input prices and only slightly increasing demand for dairy products. According to the efficient structure hypothesis, farms with superior performance and higher efficiency increase their market share at the expense of less efficient farms (Goddard et al. 1993). At the same time, however, there is empirical evidence that inefficient farms persist in the market, at least in the short run (e.g., Emvalomatis et al. 2011).

Several authors have attempted to identify economic efficiency and its determinants by targeting farm size, managerial ability, production intensity or financial structure (e.g., Mosheim and Lovell 2009; Lambert and Bayda 2005). However, the majority address efficiency measurement in a static way. That is, the role of time and the adjustment processes of farms with respect to quasi-fixed factors are not taken into account. Dairy farms are characterized by high levels of endowment in quasi-fixed factors such as land, buildings or livestock, and standard efficiency analyses assume that these factors can be adjusted to the optimal level instantaneously even though this is not the case. In addition, this factor adjustment entails further costs attached to the adjustment—that is, the adjustment costs. If these costs and dynamic production constraints are disregarded, biased parameter estimates may result, implying that firms[1] that actually behave optimally may appear inefficient (Gardebroek and Oude Lansink 2008; Skevas et al. 2012).

The intertemporal linkages of production and (dis)investment decisions are emphasized by the concept of dynamic efficiency (e.g., Silva and Stefanou 2007). Dynamic efficiency models

[1] The terms "firm" and "farm" are used interchangeably in this thesis.

explicitly consider that decisions made today affect future states: today's investment increases the capital stock not only today, but also in the future. Furthermore, investments change a firm's financial situation, for example, the firm's solvency (Gardebroek and Oude Lansink 2008). Measuring dynamic efficiency acknowledges that changes in the quasi-fixed factor level entail adjustment costs since the firm has to spend internal resources to aquire and adapt the new capital. Several authors have attempted to combine intertemporal dependencies and efficiency measurement (e.g., Silva and Stefanou 2007 or Rungsuriyawiboon and Stefanou 2007; 2008).[2] For instance, Rungsuriyawiboon and Stefanou (2007; 2008) establish a dynamic efficiency model by integrating the static shadow cost approach into the dynamic dual model of intertemporal decision making. While the first approach allows the researcher to decompose economic efficiency into technical and allocative efficiency, the second approach considers the time dimension and distinguishes the optimal factor demand between variable and quasi-fixed factors. Recently, Rungsuriyawiboon and Hockmann (2012) have used this modeling approach to investigate structural change and technical change in Polish agriculture.

However, the existing contributions to dynamic efficiency measurement are built on the assumption of static price expectations; that is, current prices and outputs are assumed to persist in the future. By assumption, decision makers do not revise their expectations, and hence, neither price nor yield uncertainty play a role. However, this is clearly unrealistic because farmers have to make their production and investment decisions in an uncertain economic environment (Serra et al. 2014; Skevas et al. 2012; Skevas et al. 2014). This is particularly true for the dairy sector in the EU, where reduced price support and increasing quota levels have led to increasing milk and factor price volatility (e.g., Keane and O'Connor 2009; Jongeneel et al. 2010). As commonly found in the literature, uncertainty affects the optimal demand of variable inputs, and even more so the demand of quasi-fixed production factors (e.g., Pindyck 1991; Serra et al. 2010; Serra et al. 2014). Empirical evidence for a negative investment-uncertainty relationship is provided, for example, by Pietola and Myers (2000), who analyze dynamic adjustment in the Finnish pork industry.[3] The effect of uncertainty on optimal factor demand will, in turn, have an influence on the measurement of dynamic efficiency since the latter is

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2 This strand of literature models the production process parametrically. Alternatively, non-parametric models based on data envelopment analysis (DEA) have been developed, e.g., Nemoto and Goto (2003), Ouellette and Yan (2008), Skevas et al. (2012).

3 A large body of research investigates the interplay between investment and uncertainty. In the agricultural sector, a negative impact has been found by Sckokai and Moro (2009). These authors analyze arable farms in Italy and report that the variance of the cereals and oilseeds price negatively affects investment in buildings. Boetel et al. (2007) estimate U.S. hog supply and show that hog price uncertainty negatively affects the demand for investment in breeding livestock and output supply.

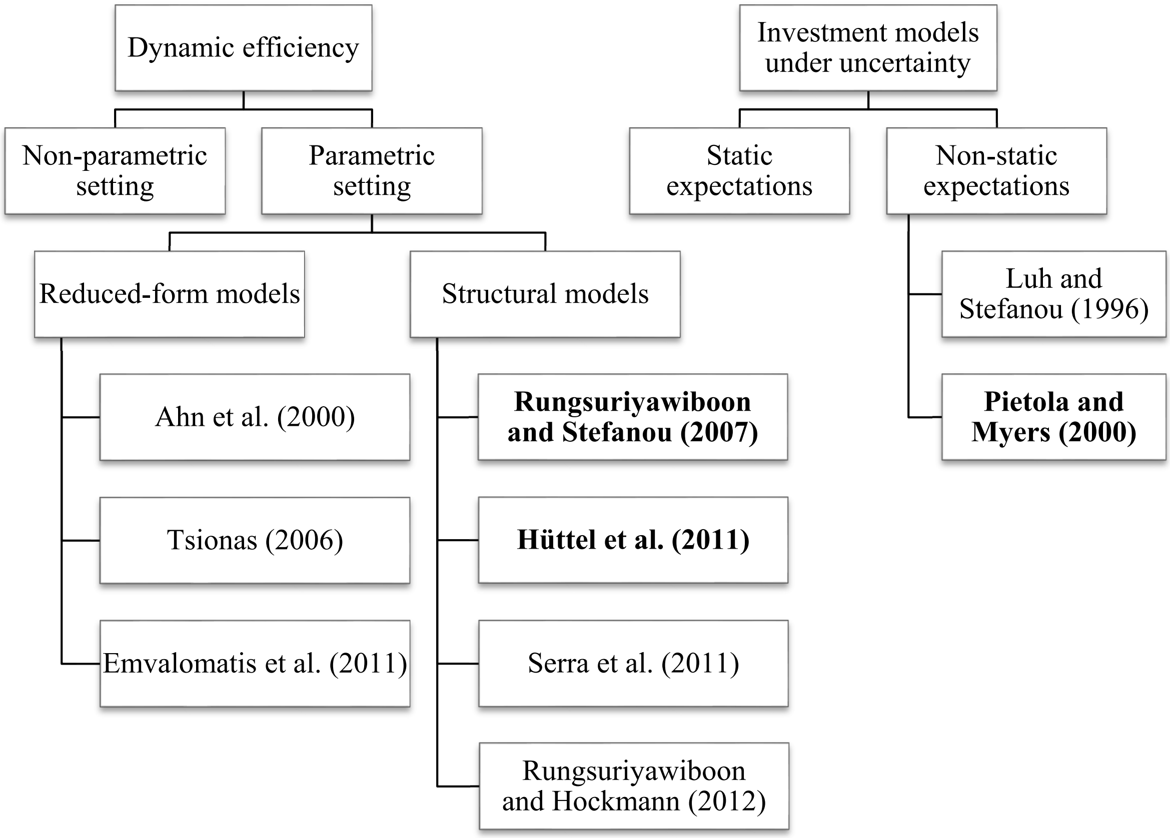
based on optimal factor demand functions: Chen and van Dalen (2010) show in a static context that efficiency analyses based on a deterministic DEA may lead to biased efficiency scores in the presence of output uncertainty. It can be conjectured that a similar effect applies in a dynamic context, that is, farms' long-run and short-run factor adjustments may appear seemingly inefficient.

1.2 Aim of the thesis

Static approaches are commonly used to measure the economic efficiency of dairy farms. This work differs from standard (static) approaches by accounting for intertemporal decision making, that is, it explicitly accounts for the interdependence of production decisions over time. In addition to accounting for dynamic efficiency there is another challenge, namely accounting for uncertainty. Figure 1 depicts the relevant studies in the research of dynamic efficiency and investment under uncertainty. The studies by Rungsuriyawiboon and Stefanou (2007), Pietola and Myers (2000) and Hüttel et al. (2011) have to be accentuated (bold letters in Figure 1). Rungsuriyawiboon and Stefanou (2007) conduct a study in which they model and estimate dynamic efficiency in the duality framework; however, uncertainty of prices and yields does not play a role. Pietola and Myers (2000) employ a dual model of investment to incorporate uncertainty in the optimal factor demand equations; however, these authors assume perfectly efficient firms.

A dynamic efficiency model enhanced by Hüttel et al. (2011) provides a new direction. The basic idea is to merge models of investment under uncertainty and (deterministic) dynamic efficiency analysis. The study closest to theirs is Rungsuriyawiboon and Stefanou (2007), where the authors integrate the static shadow cost approach of efficiency measurement into a dynamic dual production model. Hüttel et al. (2011) take up their approach and expand on it by introducing non-static expectations on prices and output. The model results in a recursive system of factor demand equations, that is, the optimal levels of the variable factors depend on each other and are both determined by the optimal quasi-fixed factor demand. The demand functions further depend on the respective factor prices, their variation and the respective covariances. By means of this model, the literature on dynamic efficiency is extended by introducing non-static expectations and the literature on stochastic dual models for investment (e.g., Pietola and Myers 2000) is extended by including technical and allocative inefficiency measures. No empirical application of this dynamic efficiency model under uncertainty has been carried out.

Figure 1. Overview of relevant literature



This thesis aims to empirically analyze the dynamic efficiency of German dairy farms. Dairy farming is an important agricultural sector with a high contribution to the agricultural production value, and dairy farms operate under dynamic and uncertain conditions. To investigate the effect of uncertainty in the optimal factor allocation process of German dairy farms, the dynamic efficiency model under uncertainty developed by Hüttel et al. (2011) is applied. The research questions with respect to West German dairy farms are as follows:

i. How does adjustment pressure and optimal factor allocation affect the West German dairy sector?
ii. How large is the technical efficiency of net investment and variable factors?
iii. Do the farms over- or underuse their resources?
iv. Does uncertainty affect the dynamic efficiency measurement of dairy farms?

1.3 Outline

The thesis is organized as follows. Section 2 describes the dairy sector, including the political environment and price developments (2.1), the farm structure in Germany (2.2) and recent relevant efficiency studies (2.3). In section 3, the state of the art of efficiency analysis is explored; this includes the theoretical background for efficiency measurement (3.1), a review on static efficiency approaches and the consideration of uncertainty (3.2), as well as a review of dynamic efficiency studies (3.3). Thereby, the variety of research is described and the gap in the literature on dynamic efficiency and uncertainty is highlighted. The theoretical model of dynamic efficiency under uncertainty is then described in section 4, containing the theoretical model derivation (4.1), the value function specification (4.2.) and hypotheses (4.3). Next, the empirical application for West German dairy farms is presented, including the data and variable description (5.1), the empirical model (5.2) and the estimation procedure (5.3). In section 6, the results for West German dairy farms with respect to efficiency and uncertainty effects are discussed. Therein, the estimated value function parameters (6.1), the average efficiency scores, as well as the efficiency scores by categories (6.2) are presented. Moreover, the interplay between efficiency and uncertainty is analyzed (6.3) and a critical reflection on the employed model is given (6.4). Section 7 provides conclusions and directions for future research.

2 The German dairy sector

The dairy sector is dynamic and subject to policy changes. Since 1984, the milk quota has restricted milk production on the farm level. The 2003 CAP reform and the ensuing 2008 health check gave fundamental direction to the sector. Emerging commodity price uncertainty, one result of the de-regulation, is rather new for dairy farms compared to other sectors such as hog fattening (Keane and O'Connor 2009). This adds pressure at the farm level. Increasing productivity and efficiency are hence essential for the farms to cope with this situation. To interpret the results of the efficiency analysis of German dairy farms conducted in this thesis, knowledge about the dairy sector is mandatory. Hence, the political background for dairy farms with respect to the CAP and its reforms is described (2.1). Following that, milk production levels in the EU and Germany are reported, and the German dairy sector's farm structure and its development are presented (2.2). Here, focus is mainly on developments between 1996 and 2010 because the efficiency analysis in this thesis is carried out for this period. Finally, efficiency studies for dairy farms are reviewed (2.3) highlighting the research gap and showing the rather diverse picture of dairy farms' efficiency.

2.1 Political environment

The German agricultural sector is framed by the CAP of the EU, which came into force in 1962. The CAP is based on three principles: a homogeneous market (free circulation of agricultural products within the EU member states), community preference (preferential treatment of EU agricultural products compared to imports) and financial solidarity (expenditures for the CAP are financed by the EU budget) (BMEL 2014a). Initially, agricultural production was promoted by minimum prices above the world price and by purchase guarantees. The first common market organization was established for wheat in 1967, followed by market organizations for other agricultural commodities such as sugar (BMEL 2014a).[4] The common market organization for milk and milk products was introduced in 1968 by Council Regulation (EEC) No 804/68. Intervention prices for milk and a boundless purchase guarantee were set up to support farmers. Along with this, productivity increases led to a surplus of milk production (BMEL 2014a). This resulted in high public expenditures for storage, elimination and export

[4] Since 2007 a single common organization of agricultural markets has been in force and combines the former common market organizations by Council Regulation (EC) No 1234/2007 (European Commission 2012b).

subsidies for promoting exports (DRV 1991). To control expenditures, restricting milk production has sometimes been necessary.

In 1984 production quotas for milk were imposed with the aim to balance demand and supply in the EU (BMEL 2014a; Council of the European Communities 1984). Initially, every member state received a national production quota based on the milk sales (deliveries and direct sales) in 1983, plus 1% based on Council Regulation (EEC) No 854/84 (Council of the European Communities 1984; Alliance Environnement 2008). The quotas have been allocated differently within the EU member states, based on two systems: formula A, individual farm quotas, e.g., in Germany—or formula B, quotas on the creamery level, e.g., in Denmark and Ireland (DRV 1991). The statutory basis for executing the EU milk quota regime in Germany is based on regulating guaranteed quantities for milk (in German: *Milch-Garantiemengen-Verordnung*).[5] The initial quota levels correspond to the individual farm's milk production in 1983 minus a percentage reduction depending on farm size and increase in milk supply between 1981 and 1983. The reduction ranged between 2.5–12.5% (Kleinhanß et al. 2010; DRV 1991). In 1984/85, the milk quota in Germany amounted to 23.487 million tons (DRV 1991). If milk deliveries exceeded this milk quota a penalty—the super levy—had to be paid (Kleinhanß et al. 2010). In the beginning of the milk quota regime, milk quotas were attached to land—a quota transfer was only possible with a transfer of land at the same time (Kleinhanß et al. 2010). In 1990/91, leasing contracts for milk quotas were introduced (DRV 1991).

Since 1984, the quota regime has been subject to policy changes. In the beginning, the quota was scheduled for five years (Council of the European Communities 1984). A first CAP reform took place in 1992, known as the MacSharry reform, which introduced a shift from product support to producer support (European Commission 2012b). For example, the support price for cereals and beef were reduced by 33% and 15%, respectively. To offset these reductions, direct payments for farmers were established (BMEL 2014a). In addition, the milk quota system was extended until 2000. Furthermore, in 1992/1993 the transfer of milk quotas without land was introduced.

As part of Agenda 2000, the 2000 CAP reforms—agreed on at the Berlin Council in March 1999—introduced environmental aspects and rural development as a second pillar of the CAP additional to the first pillar of market price support (European Commission 2012b). The support price for wheat and beef, and also for milk were decided to be further reduced—by 15% over

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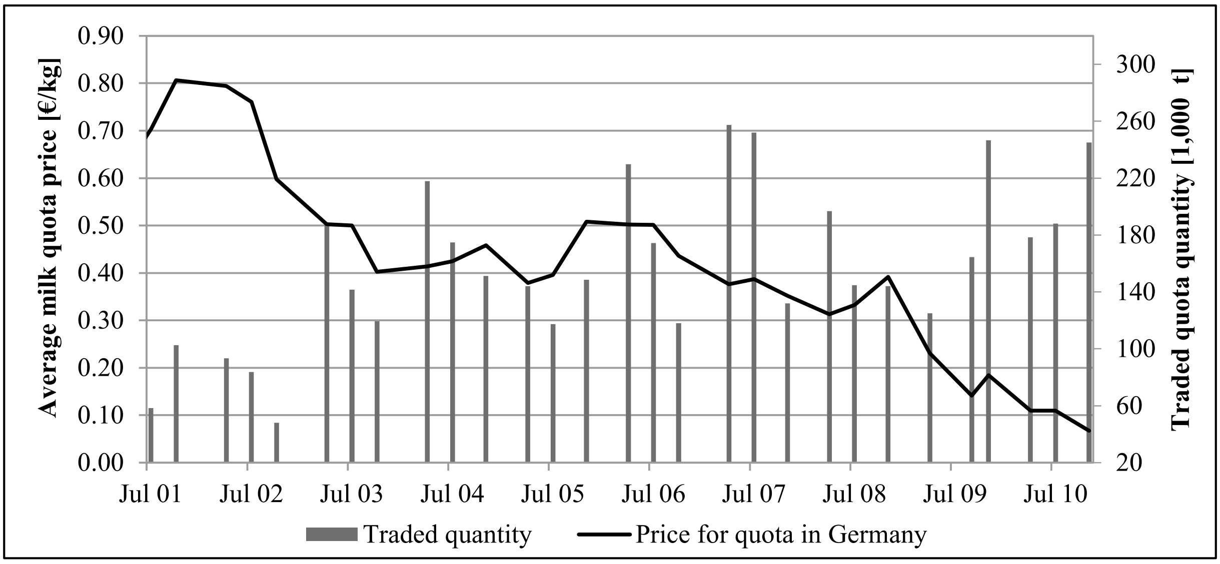
5 The regulation was replaced in April 2000 (*Verordnung zur Durchführung der Zusatzabgabenregelung*) and renamed in March 2008 (*Milchquotenverordnung*).

three years—along with an increase in the direct payments. Furthermore, the milk quota system was extended until 2008. In addition, the member states could attach voluntary environmental regulations to direct payments (BMEL 2014a). In April 2000 the transfer of quotas in Germany based on leasing contracts was banned, and since then milk quotas can only be traded landless at regional transfer agents three times a year.

Further changes were introduced by the 2003 CAP reform. Within the Luxembourg Agreement of the Midterm Review of the Agenda 2000, Council Regulation (EC) No 1787/2003 decoupled income support payments from production levels, and further reduced intervention prices for dairy products. To offset the reduced dairy support prices, a dairy premium based on the individual reference quantities per farm was established. Further key elements of the reform are the introduction of cross-compliance—a link between payments to farmers and environmental aspects—and the modulation—transfer of CAP funds from the first pillar to the second pillar (BMEL 2014a). In addition, the EU member states agreed on a further prolongation of the milk quota system until 2015 (BMEL 2014a; Witzke et al. 2009). Since July 2007 the former 21 regional trading zones for milk quotas in Germany have been aggregated into two trading zones: West and East Germany.

Further policy adjustments were decided in 2008 within the health check of the 2003 CAP reform. A major aspect for dairy farming has been the decision to abolish the milk quota in 2014/15. The stepwise quota enlargement until 2014/15 by 1% every year between 2009/10 and 2013/14 has been introduced to ensure a soft landing, with zero quota prices in 2015 (European Commission 2009). Figure 2 depicts the milk quota price development and the traded quantity in Germany between 2001 and 2010. In July 2001 the quota price was 0.703 Euros per kg, which was decreased to 0.396 Euros per kg in July 2005. In November 2010 0.067 Euros per kg were reported. The traded quantity amounted to 58,300 tons in July 2001, which increased to 245,145 tons in November 2010.

Figure 2. Milk quota price and traded quantity in Germany

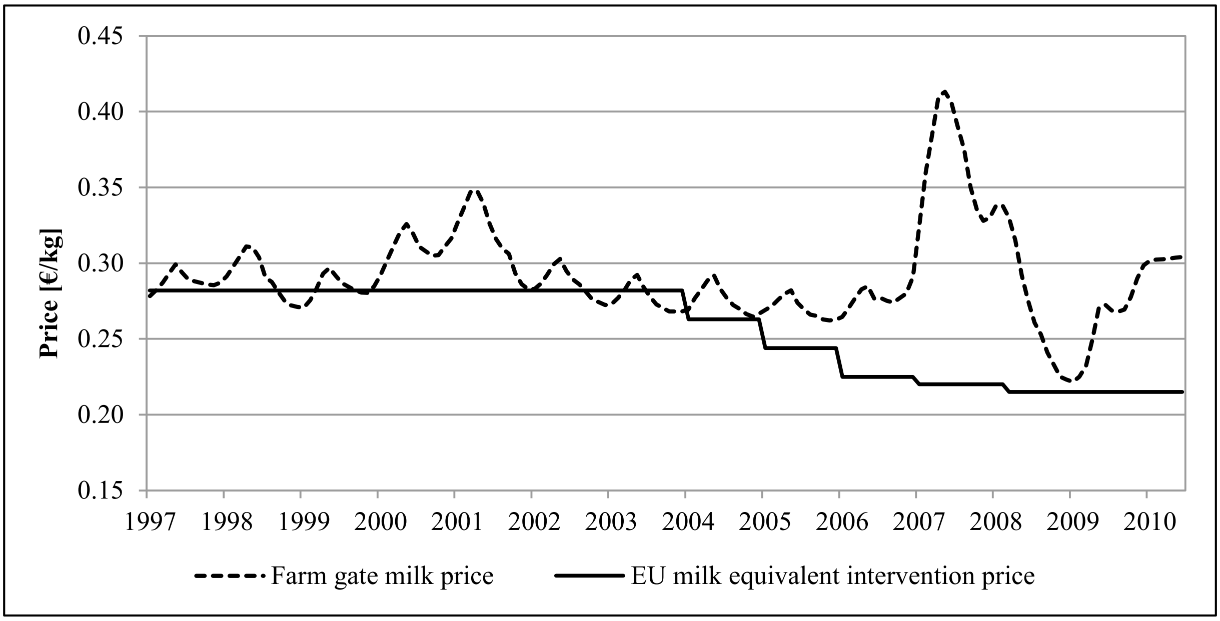


Source: Deutscher Bauernverband (2013).

In June 2013 the European Commission, the European Parliament and the European Council agreed on further CAP reforms to define the CAP between 2014 and 2020 (European Commission 2013). A central element is the greening of direct payments linked to the fulfillment of environmental requirements, for example, preserving permanent grassland or maintaining diversified production (BMEL 2014a). However, with respect to the dairy sector, the basic conditions for the following years have been decided within the health check of the 2003 CAP reform, for example the milk quota abolition.

To summarize, developments in the dairy sector have been characterized by increased trade liberalization, with the central target being to abolish the milk quota. The development of the farm gate milk prices in Germany and of the milk equivalent intervention price in the EU between 1997 and 2010 is reported in Figure 3 and indicates that prior to 2007 the farm gate milk prices were rather stable. In the beginning of 2008 the prices sharply increased, followed by a decrease approaching a minimum in the middle of 2009. The EU intervention price has fallen from 0.282 Euros per kg to 0.215 Euros per kg over time. Owing to the current developments in EU dairy policies and a more liberalized market situation, price volatility is expected to increase. This is a novelty for dairy farmers in comparison to pig producers or commercial gardeners and adds challenges for business planning (Keane and O’Connor 2009).

Figure 3. Farm gate milk price and EU milk equivalent intervention price

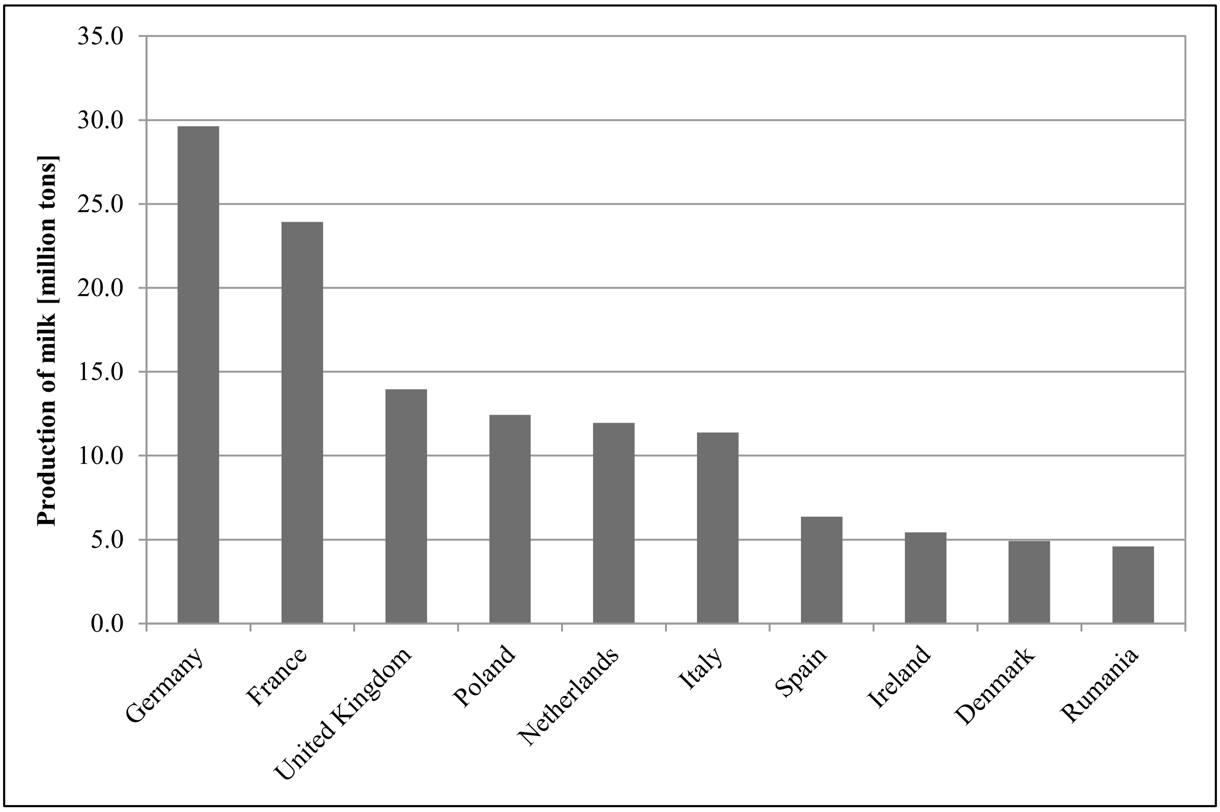


Source: European Commission (2010a), Statistisches Bundesamt (2013a), ZMP (diverse volumes).

2.2 Milk production structure in Germany

In addition to cereals and sugar beets, milk is one of the major agricultural commodities produced in the EU, with milk production reaching 136 million tons in 2010 (Eurostat 2012). Within the EU-27, Germany, France, the United Kingdom, Poland, the Netherlands and Italy account for 70% of milk production. Milk production levels differ considerably among the EU member states and Figure 4 illustrates that Germany had the highest level of milk production with 29.63 million tons in 2010 followed by France and the United Kingdom (Statista 2013). In addition to these country differences, the production level of milk differs at the regional level.

Figure 4. Milk production levels in selected EU member states

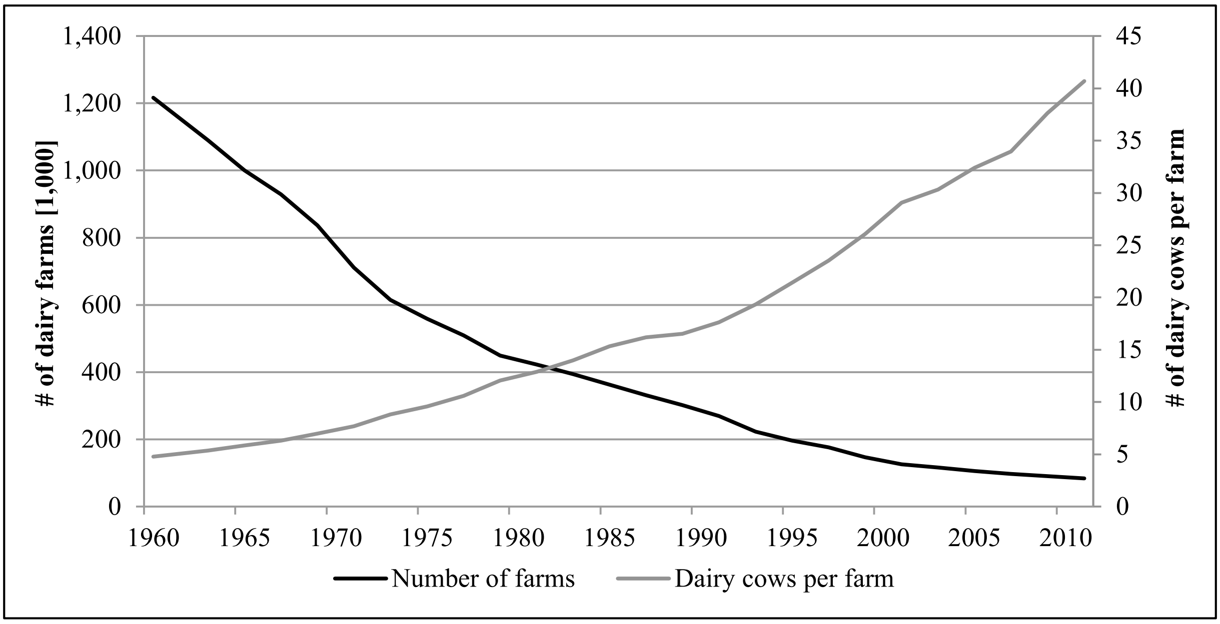


Source: Statista (2013).

The production value of the German agricultural sector amounted to 46.1 billion Euro in 2010, with milk production contributing 20% to this figure (AMI 2011). The German dairy sector is characterized by regional differences in farm structure, as well as differences in milk production levels. The East-West difference is mainly caused by historical developments. Until German reunification, farming in East Germany was characterized by agricultural production cooperatives (in German: *Landwirtschaftliche Produktionsgenossenschaften*). This organizational type was made illegal after reunification and the farms were dissolved or restructured into other legal forms such as agricultural cooperatives. East German dairy farms are still characterized by their large size and are organized into corporate bodies—e.g., agricultural cooperatives or limited liability companies—with an average farm size of 155 cows per farm in 2010. In addition, these farms are mainly mixed-product farms. In West Germany, mainly specialized dairy farms can be found. Dairy farming is characterized by smaller farms, for example in sole proprietorship, with an increasing average herd size from 5 cows (1960), to 13 cows (1981) and 38 cows per farm (2010) (Figure 5).

Both regions are experiencing declines in the number of dairy farms and the total number of dairy cows. In 1992, 9,716 dairy farms with 1.04 million cows existed in East Germany. These values decreased to 4,800 farms with 0.75 million cows in 2010. The structural development of West German dairy farms is depicted in Figure 5, which indicates that the number of dairy farms declined from 1.22 million (1960) to 0.86 million (2010). According to the Statistisches Bundesamt (2012), the total number of dairy cows has decreased from 5.8 million (1960) to 3.43 million (2010).

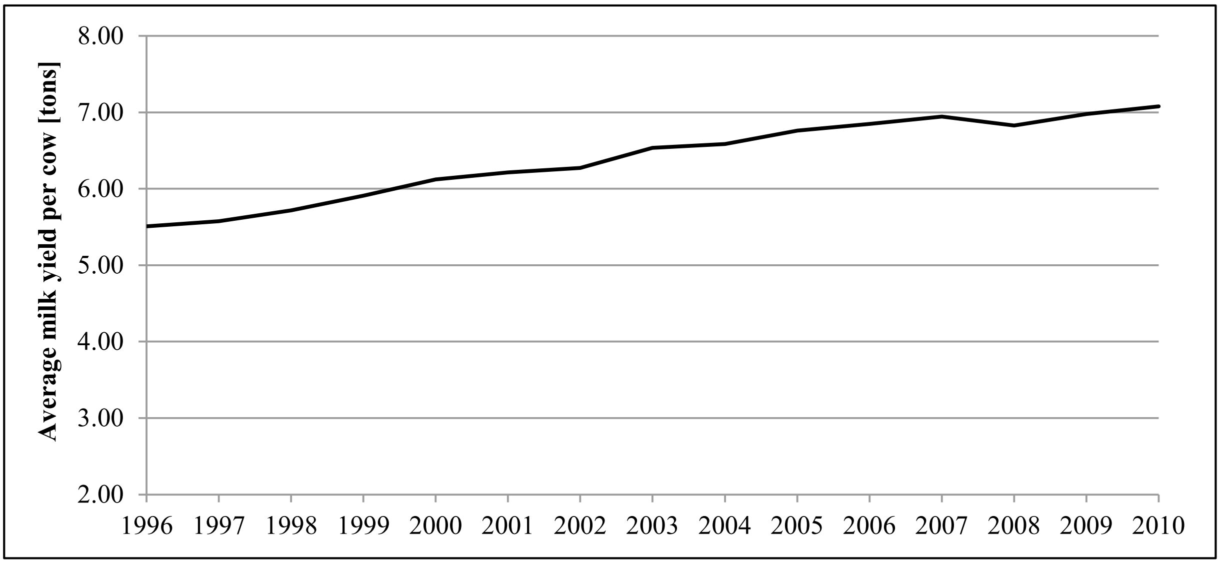
Figure 5. Structural development of West German dairy farms



Source: Statistisches Jahrbuch über Ernährung, Landwirtschaft und Forsten (diverse volumes).

The number of dairy cows decreased over time, but the production level was nearly stable. This was mainly caused by an increase in milk yield per cow. The increase in the milk yield per cow stemmed mainly from breeding improvements and different feeding and husbandry conditions (Schramek et al. 2012). Figure 6 presents the development of the milk yield per dairy cow in Germany between 1996 and 2010. In 1996, the average milk yield per cow and year amounted to 5.51 tons. This figure increased to 6.59 tons in 2004 and to 7.08 tons per cow and year in 2010. These values differ in East and West Germany: in East Germany 8.45 tons per cow and year were produced in 2010, whereas cows in West Germany produced 6.79 tons per cow and year in 2010 (Statista 2013). In comparison, the average milk yield per cow in the EU-27 amounted to 6.47 tons in 2010 (BMEL 2013).

Figure 6. Milk yield per cow and year in Germany



Source: AMI (diverse volumes).

This thesis empirically analyzes specialized Germany dairy farms. This selection enables one to relate expenditures directly to dairy activities. Specialized farms are concentrated in West Germany; in East Germany most farms are mixed-product farms. Hence, the following paragraphs focus on West Germany. On the federal state level, Table 1 depicts differences in farm structure among the West German federal states in 2010—excluding city-states. The largest number of dairy cows were present in Bavaria (1.25 million) followed by Lower Saxony (0.776 million); the smallest number of dairy cows were found in Saarland. Most dairy farms are located in Bavaria (48%), with an average farm size of 29.2 cows per farm. The largest farms with respect to the number of dairy cows are located in Schleswig-Holstein (68.6 cows per farm). In addition, Schleswig-Holstein exhibits the largest milk production per farm (492.8 tons), followed by Lower Saxony (420.3 tons). Farms located in Lower Saxony had the highest milk yield per cow. With respect to the administrative regions in Germany, farms located in Weser-Ems (Lower Saxony) and Oberbayern (Bavaria) have the highest milk yield per cow (Witzke et al. 2009).

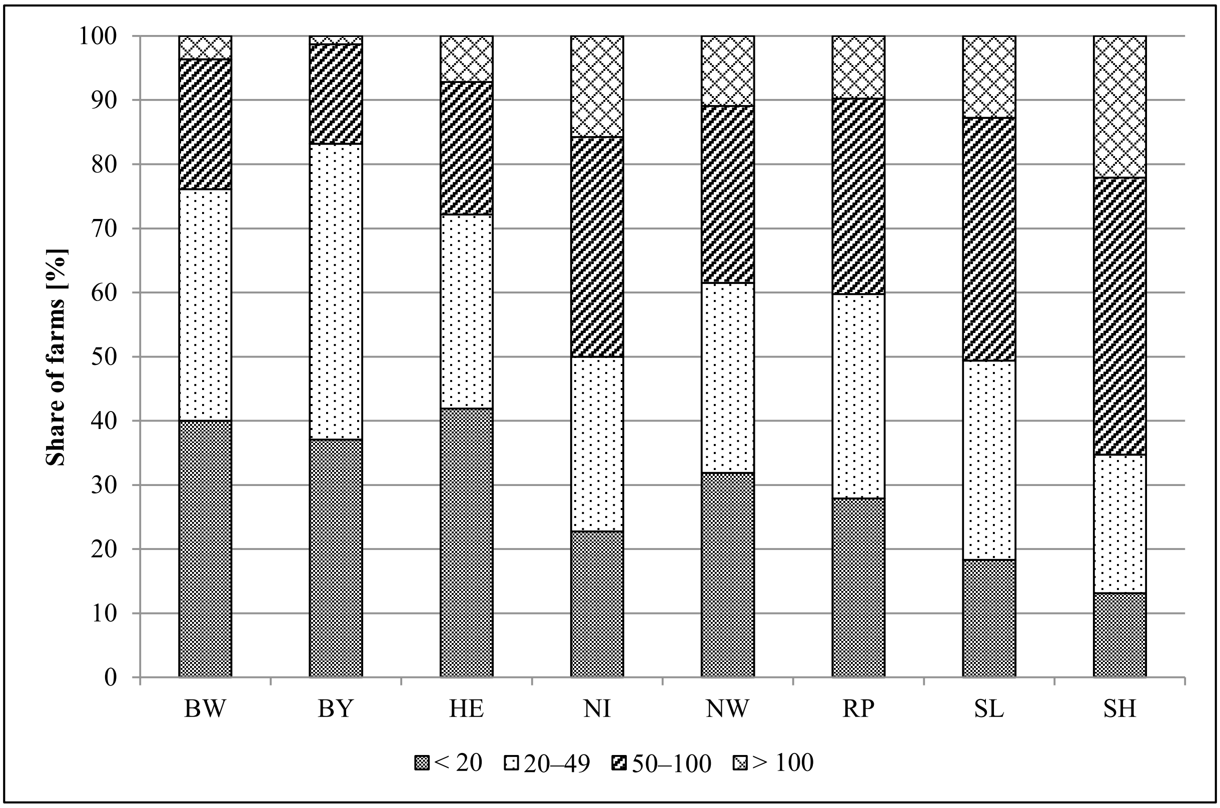
Table 1. Operation figures for West German dairy production in 2010

Federal state	Dairy cows [1,000]	Farms [1,000]	Dairy cows per farm	Milk production per farm [metric tons]	Milk yield [metric tons per cow, year]
Baden-Württemberg	353.1	11.1	32.2	200.9	6.31
Bavaria	1,248.8	42.8	29.2	181.3	6.24
Hesse	148.8	4.2	36.2	239.2	6.75
Lower Saxony	776.4	13.8	56.3	420.3	7.47
North Rhine-Westphalia	398.1	8.7	45.7	338.9	7.41
Rhineland-Palatinate	119.0	2.6	46.1	310.7	6.79
Saarland	14.3	0.3	55.3	303.7	6.38
Schleswig-Holstein	373.5	5.3	68.6	492.8	6.99

Source: Statistisches Bundesamt (2012).

Figure 7 illustrates the farm size distribution of dairy farms in the West German federal states, and indicates the following. In Baden-Württemberg, most of the farms have less than 20 cows (40%), followed by farms with 20–49 cows (36.1%). A total of 20.2% farms keep 50–100 cows, and 3.6% of the farms have more than 100 cows. In Bavaria, the majority of farms (46.1%) have 20–49 cows, followed by farms with less than 20 cows (37%) and 50–100 cows (15.4%). A small number of Bavarian dairy farms keep more than 100 cows (1.3%). The highest share of small farms (< 20 cows) is observed in Hesse. In Rhineland-Palatinate, the share of small farms (< 20 cows) amounts to 27.8%, and the share of large farms (> 100 cows) amounts to 9.7%. In Saarland, 37.8% of the farms have 50–100 cows. In Lower Saxony 15.7% of the farms have more than 100 cows, and 34.3% have 50–100 dairy cows; 22.7% of the dairy farms have less than 20 cows. North Rhine-Westphalia shows an equal distribution among the first three size classes—around 30% of the farms per class—with larger farms accounting for 10%. The highest share of farms with more than 100 cows among the West German federal states is observed in Schleswig-Holstein (22.1%). In addition, Schleswig-Holstein has the lowest share of small farms with less than 20 cows (13%). The southern parts of Germany contain a larger number of farms with lower herd size (< 20 cows) and a smaller number of large farms (> 100 cows). In the northern parts, for example in Schleswig-Holstein, the opposite is true (Statistisches Bundesamt 2012).

Figure 7. Farm size distribution in West German federal states



Note: The federal states are abbreviated according to ISO 3166-2: BW: Baden-Württemberg, BY: Bavaria, HE: Hesse, NI: Lower Saxony, NW: North Rhine-Westphalia, RP: Rhineland-Palatinate, SL: Saarland and SH: Schleswig-Holstein.
Source: Statistisches Bundesamt (2012).

2.3 Efficiency studies for dairy farms

2.3.1 Research results by static approaches

The agricultural sector is one of the most studied sectors in terms of efficiency analysis (Maietta 2000). Indeed, a meta-regression by Bravo-Ureta et al. (2007) highlights that 30% of the analyzed studies are dedicated to dairy farms. An overview based on their study is presented in Appendix A, Table 12. Various studies elaborate on the economic, allocative and technical efficiency of dairy farms. In order to offset reduced farm prices due to reduced price support, increases in efficiency and the respective knowledge about the current level are necessary (Sauer and Latacz-Lohmann 2014). Knowledge on these studies is indispensable for comparing and evaluating the empirical results of this thesis. Special attention is paid to case studies conducted for German dairy farms. This review is conducted to determine whether prices and output-level uncertainty is taken into account.

International farm studies The literature hypothesizes that farm-, environmental- and animal-specific characteristics may affect efficiency. One of the factors affecting efficiency often discussed in the literature is farm size. However, the existing studies offer mixed results. For example, Hadley (2006) reports that herd size positively affects the technical efficiency of British farms. Alvarez and Arias (2004) reach a similar conclusion for Spanish dairy farms using a model based on Lau and Yotopoulos (1971). From their theoretical model, Alvarez and Arias (2004) expect that with increasing efficiency the farms increase the amount of variable inputs and improve usage and hence produce more output; that is, a positive relation exists between technical efficiency and size. The model is implemented by using panel data from 196 dairy farms located in northern Spain. The authors estimate an average technical efficiency of 0.70, and found empirical evidence that technical efficiency and size are positively correlated. Mosheim and Lovell (2009) examine the economic efficiency of 619 U.S. dairy farms. Their model is based on a shadow cost function by Kumbhakar and Lovell (2000), from which these authors obtain average efficiency scores of 0.75, 0.56 and 0.46 for technical, allocative and economic efficiency, respectively. Mosheim and Lovell (2009) present evidence that larger farms are more efficient than small and medium-sized farms; that is, efficiency is increasing with farm size measured by number of cows. Maietta (2000) examines cost efficiency for a panel of 41 Italian dairy farms; using the shadow cost approach, this author decomposes cost efficiency into technical and allocative efficiency. The results highlight that costs increase by 69% and this is mainly a consequence of technical inefficiency. Allocative inefficiency amounts to 0.17. Furthermore, Maietta (2000) found that technical and allocative inefficiencies differ among farm size measured by hectares of land. In addition, medium-sized farms show the highest technical inefficiency but the lowest allocative inefficiency.

The relation between efficiency and management, such as education, experience—representing the managers' ability—and managerial practices, is further examined in the literature. Stefanou and Saxena (1988) analyze 131 Pennsylvania dairy farms using data from 1982 by employing a profit function approach. The results indicate that education and experience play a significant role for the efficiency level: additional education and experience increase allocative efficiency. In addition, farmers with a higher level of post-secondary education—college or university—require less years of management experience to reach relative efficiency. Reinhard and Thijssen (2000) examine the cost efficiency of a panel of 434 dairy farms in the Netherlands by using a shadow cost approach. Their results show that the technical efficiency of Dutch milk producers was 0.84, while allocative efficiency was 0.95, suggesting that Dutch dairy farms adjust their input mix according to price changes. According to these authors, the experience of farm managers, agricultural education and milk yield are positively related to technical efficiency, whereas age is negatively related. Luik et al. (2014) present empirical evidence that the milk quality is important: higher somatic cell counts decrease and a higher content of milk solids increases technical efficiency. In addition, the cow's breeding value positively affects technical efficiency. The effect of managerial practices such as animal health—e.g., age at the first calving—, breeding, and feeding practices on economic efficiency at Swedish dairy farms is analyzed by Hansson and Öhlmer (2008). Using data for 505 farms, these authors found that analyzing forage positively affected allocative efficiency and analyzing fodder grain positively affected economic efficiency, whereas feeding hay instead of silage reduces economic efficiency. However, no significant effects of animal health practices were found. In contrast, Barnes et al. (2011) highlight that animal health can contribute to increases in technical efficiency: farms with low rates of lameness—below 10% of the cattle herd—tend to have significantly higher technical efficiencies than those with lameness rates of above 10% of the herd (0.93 versus 0.78).

Apart from these findings, efficiency may vary with production intensity. Alvarez and del Corral (2010) analyze 130 Spanish dairy farms from 1999–2006 to investigate the difference in technical efficiency originating in the degree of intensification. Intensification is measured through purchased feed per cow and stocking—number of cows per hectare. These authors report that intensive farms are significantly more technically efficient compared to extensive farms—0.97 versus 0.93; they reason that intensive systems are easier to manage compared to extensive systems. These farms perform less tasks with respect to planting and harvesting forage crops produced on the farm because these farms may mainly use purchased feed. According to Alvarez and del Corral (2010), intensive farms are more likely to stay closer to the efficiency frontier.

German farm studies The aforementioned static efficiency studies focus on North America and European countries, for example the Netherlands and Spain. The following studies explicitly analyze the efficiency of German dairy farms, with the majority having been conducted for farms located in the federal state of Schleswig-Holstein (northern Germany); rather high efficiency values were found. Brümmer and Loy (2000) analyze the technical efficiency of dairy farms in Schleswig-Holstein between 1987 and 1994 using a stochastic frontier model. These authors test whether participants of the European farm credit program show higher technical efficiency, and found that participation in the program reduced efficiency, although farms show a high level—0.96—of technical efficiency. Brümmer et al.

(2002) analyze the data of 50 dairy farms between 1991 and 1994 in Schleswig-Holstein, Poland and the Netherlands using an output distance function framework to decompose productivity growth into technical change, technical and allocative efficiency. Milk producers show an average technical efficiency of 0.95 and the productivity growth is about 0.06 per annum—mainly caused by technical change. In comparison, productivity growth in the Netherlands is driven by the allocative efficiency component. For Germany, Brümmer et al. (2002) conclude that—based on the contribution of the single components to productivity growth—policy attempts promoting technological progress through extension programs or advisory circles should be favored. Similar efficiency results were obtained by Tietjen (2004), who analyzes the technical efficiency of 158 dairy farms located in Schleswig-Holstein between 1990 and 1999. Based on a DEA, this author shows that the farms' efficiency levels vary between 0.86 (1996) and 0.90 (1998); however, no significant trend has been found.

Using a stochastic frontier framework, Abdulai and Tietje (2007) examine the technical efficiency of 149 dairy farms in Schleswig-Holstein from 1997–2005. These authors also examine whether the production frontier parameters change if a model captures unobserved heterogeneity, such as soil conditions and managerial characteristics. These authors hypothesize that omitting heterogeneity leads to biased production frontier estimates and to overestimated technical inefficiency. The results indicate that the estimated parameters differ among the models (e.g., between the Battese and Coelli (1995) model and a model without heterogeneity). In addition, differences in technical efficiency are observed: the efficiency scores vary between 0.68 and 0.94 depending on the model specification. In line with their hypothesis, these authors found that models that do not control for firm-specific heterogeneity overestimate inefficiency.

Among the German case studies, the interplay between efficiency and farm-specific factors is analyzed. Lakner (2009) analyzes the interplay between agglomeration effects and technical efficiency of ecological dairy farms in Germany. The author found that technical efficiency amounts to 0.64 and that a higher share of ecological farms in the neighborhood positively influences efficiency. The relationship between technical efficiency and the economic success of dairy farms in southern Germany (Bavaria) is analyzed by Kellermann et al. (2011). These authors use data between 2000 and 2008 and apply a stochastic frontier approach. Findings report an average technical efficiency of 0.88 and reveal a positive relation between technical efficiency and economic success, where both improve with full-time farming and soil quality. Sauer and Latacz-Lohmann (2014) examine the relation between efficiency and innovation on the farm level based on a directional distance function framework. The results indicate that technical efficiency amounts to 0.91, on average. Full-time farming, investments in innovative technologies—barn and milking techniques—and level of education are found to increase technical efficiency. The farmers' agricultural education is classified into four groups: still in training to achieve a first agricultural related education; skilled worker; master craftsman diploma (in German: *Meister*); and university/applied university degree. Sauer and Latacz-Lohmann (2014) state that educational training is important for achieving technical efficiency gains based on innovations.

Furthermore, several authors attempt to compare the efficiency of German and European dairy farms. For instance, Kovacs and Emvalomatis (2011) estimate the technical efficiency of German, Dutch and Hungarian dairy farms between 2001 and 2005. Using DEA, these authors find that technical efficiency is higher for Dutch dairy farms compared to German dairy farms—0.89 vs. 0.80. In contrast, Zhu et al. (2012) found a higher average technical efficiency for German dairy farms compared to Dutch farms—0.61 vs. 0.55—using data from 1995–2004.

To summarize, even though a large variety of research exists, none of the presented studies consider the effect of factor price and output-level uncertainty on the efficiency scores.

2.3.2 Research results by dynamic approaches

The aforementioned studies share one assumption: the static view of efficiency. The dynamic efficiency literature accounts for the time interdependence of production decisions and the existence of adjustment cost, which occur if the stock of quasi-fixed factors is changed. Examples for adjustment costs are foregone output, administrative costs, or search costs (Gardebroek and Oude Lansink 2008). Milk production is characterized by a high long-term commitment of capital and a high endowment of quasi-fixed factors such as land, buildings and livestock. These production factors cannot be adjusted instantaneously and are remunerated as soon as the firm produces positive output (e.g., Rungsuriyawiboon 2003). This results in a high rate of irreversibility of investments, which makes it likely that adjustment costs occur. Very few academic studies have thus far examined the dynamic efficiency of dairy farms.

International farm studies Based on their own earlier study (Silva and Stefanou 2003), Silva and Stefanou (2007) develop nonparametric dynamic measures of technical, allocative and economic efficiency. The application is conducted for 61 Pennsylvania dairy farms for the period 1986–1992. The farm size ranges between 40 and 100 cows, and the farms derive at least 80% of their total revenue from milk production. According to their findings, the technical and allocative efficiency scores indicate a stable efficiency level over time. Technical efficiency is found to be superior to allocative efficiency. These authors reason that dairy operators have a higher managerial ability to avoid waste than to combine inputs in optimal proportions given their prices. Silva and Stefanou (2007) state that one shortcoming of their study is that neither price nor production uncertainty are taken into account: this may affect the optimal decision for variable inputs and investment, and hence the economic performance of (dairy) farms.

Based on a directional distance function, Serra et al. (2011) derive technical and allocative efficiency measures. The application focuses on 639 Dutch dairy farms from 1995–2005. The selected farms derive at least 80% of total farm income from milk production. According to their findings, productivity decreases over time due to declining efficiency. The average cost efficiency of Dutch dairy farms amounts to 0.878 and indicates that the same level of output could be achieved with 12.2% less costs. Technical efficiency amounts to 0.90, and is the main reason for cost inefficiency. Allocative inefficiency amounts to 0.018 and indicates less potential to reduce costs by an improved input mix. These authors reason that the economic environment of Dutch dairy farms has been relatively stable between 1995 and 2005 with less variation in output and input prices across the years.

Besides the cost minimization perspective of the aforementioned studies, Ang and Oude Lansink (2014) use a profit maximization approach to measure dynamic profit inefficiency for Belgian dairy farms. These authors argue that inefficiency in output production might result from the distorting effects of the milk-quota system. Starting from an intertemporal profit maximization problem these authors derive profit inefficiency measures using DEA. Using data from 1996–2008, profit inefficiency is 0.41 and mainly caused by output inefficiency than by input inefficiency. Moreover, these authors state that profit inefficiency decreases with farm size. Nevertheless, Ang and Oude Lansink (2014) do not consider price uncertainty, even though output prices such as milk prices have been subject to fluctuations in recent years. These considerations may affect the measurement of farms' performance as highlighted for example by Silva and Stefanou (2007).

German farm studies The only academic study for German dairy farms exploring dynamic efficiency has been conducted by Emvalomatis et al. (2011). These authors use a stochastic distance function model including auto correlated inefficiency; that is, correlated inefficiency through time. The data used for their study are part of the farm accountancy data network (FADN) from 1995–2005. The final data set contains 1,439 German dairy farms and 429 Dutch farms that derive at least 80% of their total revenues from milk and meat production.

Two outputs are used: revenues from milk production and meat production. Six input categories are defined: buildings and machinery; labor; utilized agricultural area; materials and services; livestock units; and purchased feed. Furthermore, the authors include regional dummy variables—eastern, western, northern, and southern Germany—to capture differences in soil and climatological conditions across Germany. However, efficiency is not analyzed separately for these categories. The results indicate that German dairy farms have an average technical efficiency of 0.78 ranging between 0.19 and 0.97. In addition, these authors calculate an expected long-run efficiency score of 0.78. According to their findings, technical inefficiency persists over time and highlights that the adjustment process toward more efficient production is costly. In line with the aforementioned international studies, price uncertainty is not considered.

To summarize, efficiency studies in dairy farming commonly explore a static perspective. Notable exceptions are Silva and Stefanou (2007), Emvalomatis et al. (2011) and Serra et al. (2011). However, farms operate under uncertain conditions, for example input and output price fluctuations and policy changes. The German dairy sector faces reduced price support, increasing quota levels and recently increasing milk and factor price volatility (cf. section 2.1). The influence of uncertainty on farms' performance has thus far not been embedded into the measurement of dynamic efficiency. This thesis will shed empirical light on the linkage between dairy farms factor allocation, price and output-level uncertainty, and technical and allocative (in)efficiency.

3 Efficiency analysis: state of the art

In this chapter, the state of the art of efficiency analysis is discussed to highlight the current research in static and dynamic efficiency. First, the fundamentals for analyzing efficiency from a static perspective are presented (3.1). Second, parametric and non-parametric static efficiency approaches are reviewed, relevant models are described formally and the consideration of uncertainty is highlighted (3.2). The literature overview in this section concentrates on applications of the shadow cost approach because it is one of the two building blocks of the theoretical model of dynamic efficiency under uncertainty presented in section 4. Third, dynamic efficiency approaches are reviewed—centering on parametric approaches because the applied dynamic efficiency under uncertainty presented in section 4 is based on this stream of research—and the relationship between efficiency measurement and adjustment over time is explored (3.3).

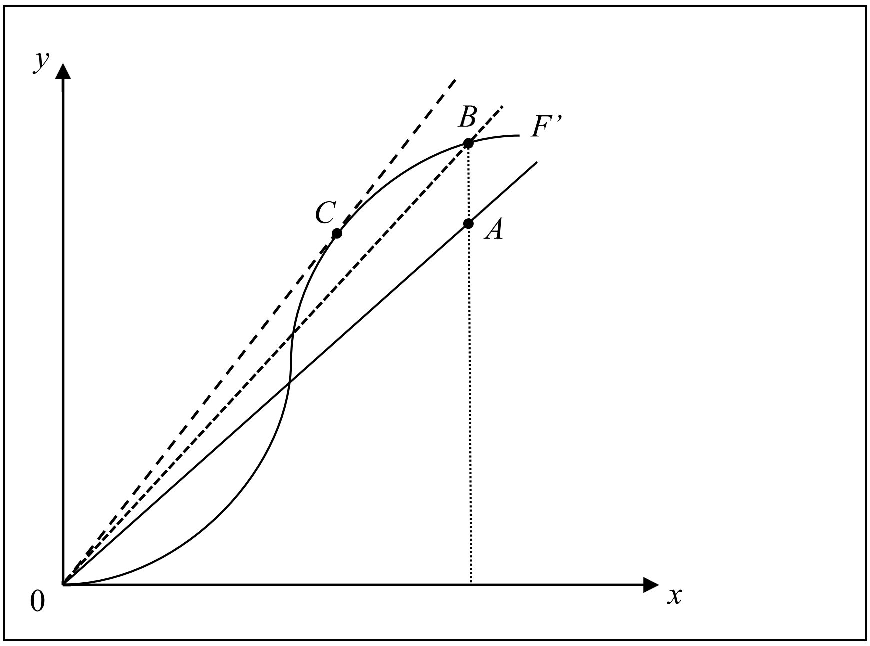
3.1 Theoretical background

3.1.1 Distinction between efficiency and productivity

The terms "efficiency" and "productivity" are often used interchangeably, however, they are not the same (Coelli et al. 2005). For the graphical illustration, a production process with one input x and one output y is assumed. In Figure 8 the production frontier, denoted by $0F'$, characterizes the technical relationship between the input and the output. Input-output combinations above the frontier cannot be realized because the production frontier defines the maximum output that can be produced with the given input (Coelli et al. 2005). Hence, the frontier represents efficient input-output combinations. Observations along the frontier, as for example denoted by B or C, characterize technical efficient production combinations: the maximum output is attained by using the given input or for a given output the minimum input is used. All combinations beneath the frontier, as for example denoted by A, are technical inefficient. In Figure 8 the three lines starting from the origin depict the productivity for a given observation trough the slope x/y and state that a higher productivity is obtained at C compared to B, even though C and B are technically efficient. It becomes apparent that productivity differences—resulting from economies of scale—exist. The highest productivity is achieved at C because the dashed line is the tangent to the production frontier. Therefore, a firm that produces at C would be characterized by a technically optimal size. Observations on the left part of C denote decreasing; observations on the right of C denote increasing returns to scale.

From this it follows that a firm can produce technically efficient but still can increase its productivity using economies of scale (Coelli et al. 2005).

Figure 8. Productivity and technical efficiency



Source: Coelli et al. (2005).

3.1.2 Technical, allocative and economic efficiency

The theoretical idea to measure efficiency dates back to Koopmans (1951), Debreu (1951) and Farrell (1957). The last-mentioned author introduced the decomposition of economic efficiency—defined as the ability of a firm to produce output at minimum cost considering an efficient production process—into a technical and an allocative component. Technical inefficiency is thereby described either by the firms' ability to obtain maximum output from given input—a proportional increase of the output level at constant input levels—or by minimizing the input use for a given output level—a proportional reduction of inputs at constant output level. The first represents the output-oriented approach and the latter the input-oriented approach (Cantner et al. 2007).[6] In addition, firms can be allocative inefficient by not purchasing the best input combination at given prices.

Farrell's decomposition for input orientation can be explained in terms of Figure 9. For the graphical illustration, a firm that operates at *P* and uses two inputs x_1 and x_2 to produce the

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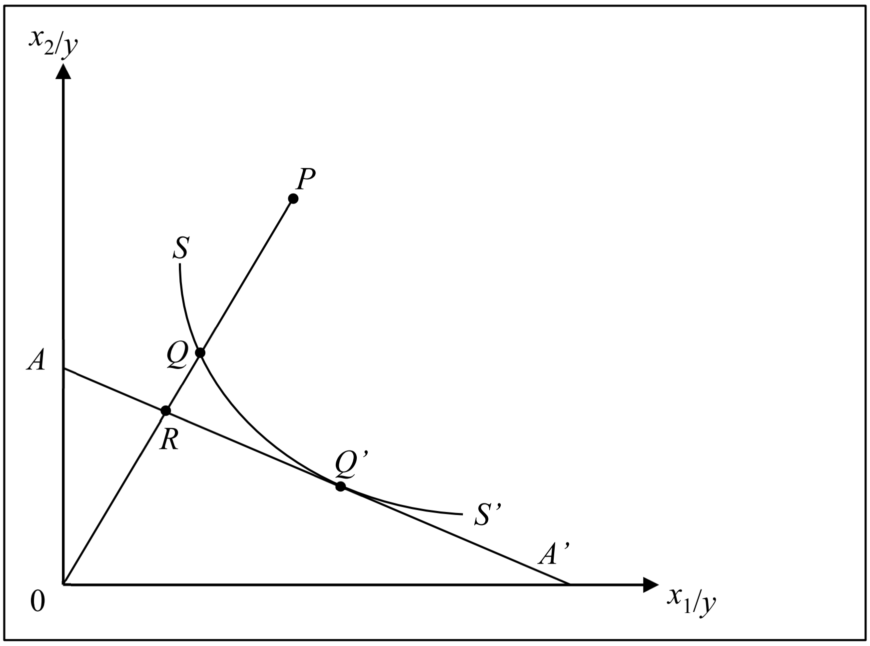
[6] The dynamic efficiency model used in this thesis is based on an input-oriented measure of efficiency, hence, the output-oriented approach will not be explained in detail here. A review of output-orientated efficiency measures is given for example by Kumbhakar and Lovell (2000) or Emvalomatis (2009).

output y is assumed. The unit isoquant of fully efficient firms is denoted by *SS'* and captures different combinations of factors that results in the same quantity of output. Observations along the unit isoquant are considered to be technically efficient, as for example denoted by Q. Technical inefficiency of a firm operating at P can be represented by the distance QP to the unit isoquant describing the quantity by which the production factors could be reduced without reducing the output to achieve a technical efficient production (Coelli et al. 2005). Hence, technical efficiency is given by

$$\mathrm{TE} = 0Q/0P. \tag{1}$$

Figure 9. Technical and allocative efficiency under input orientation



Source: Coelli et al. (2005).

Compared to technical efficiency, allocative efficiency describes the ability of a firm to use the production factors in optimal proportions given their prices. The isocost line *AA'* in Figure 9 embeds factor combinations that result in the same costs and its slope is equal to the input price ratio (Coelli et al. 2005). The optimal input mix is denoted by Q' since the marginal rate of technical substitution—the slope of the unit isoquant—is equal to the factor price relation. Therefore Q' represents a production at minimum costs. Even though Q and Q' denote technically efficient production levels, only Q' is allocative efficient. Allocative efficiency is defined as

$$\mathrm{AE} = 0R/0Q. \tag{2}$$

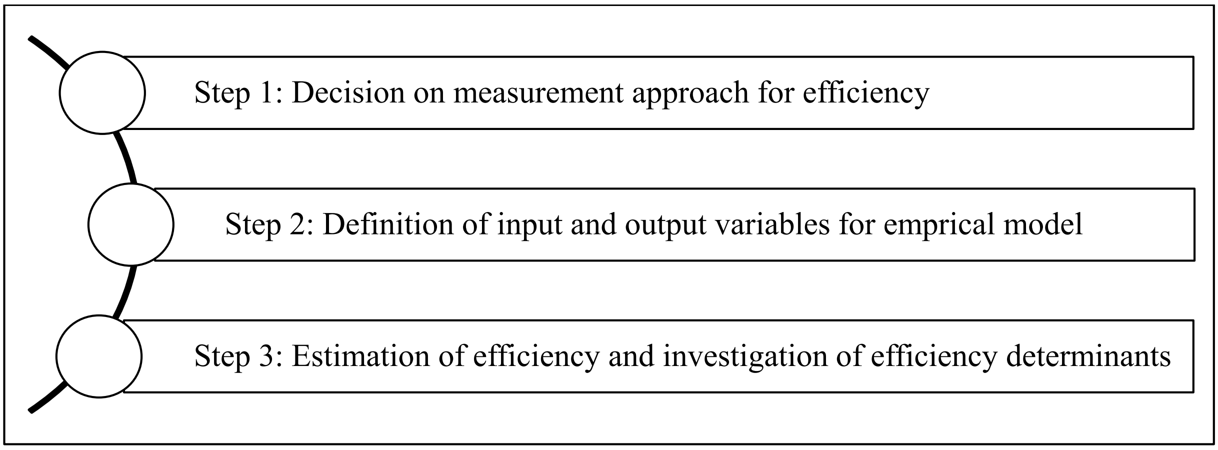
The distance *RQ* describes the possible cost reduction that arise if the firm produces at the allocative and technically efficient point *Q'* instead of *Q*. Furthermore, Farrell (1957) defined a measure for overall efficiency—renamed as economic efficiency (EE) later on in the literature—and a value of one denotes that the firm produces cost efficient, that is, produces technically efficient at minimum costs. According to Coelli et al. (2005), economic efficiency is given by

$$\mathrm{EE}=\mathrm{TE}\cdot\mathrm{AE}=\left(0Q/0P\right)\cdot\left(0R/0Q\right)=0R/0P\,. \tag{3}$$

3.1.3 Procedure of efficiency analysis

The following generalized procedure is commonly employed in the literature to analyze efficiency (Figure 10). In the first step an empirical approach for efficiency measurement based on theoretical and empirical concerns is chosen. Different models such as parametric or non-parametric approaches are available. The second step involves identifying relevant production factors and produced outputs entering the empirical model. Depending on the data availability, the researcher decides on a reasonable number and the variable measurement. The number of variables might influence the model's manageability and further determines the aggregation of variables that are important for the firm's production process. The third step includes estimating and explaining efficiency scores and possible differences. Determinants of efficiency are usually neither production inputs nor outputs. Nevertheless, these factors affect the production process and the firms' performance. Examples for these factors are organizational structure, management or regional and firm characteristics.

Figure 10. Generalized procedure of efficiency analysis



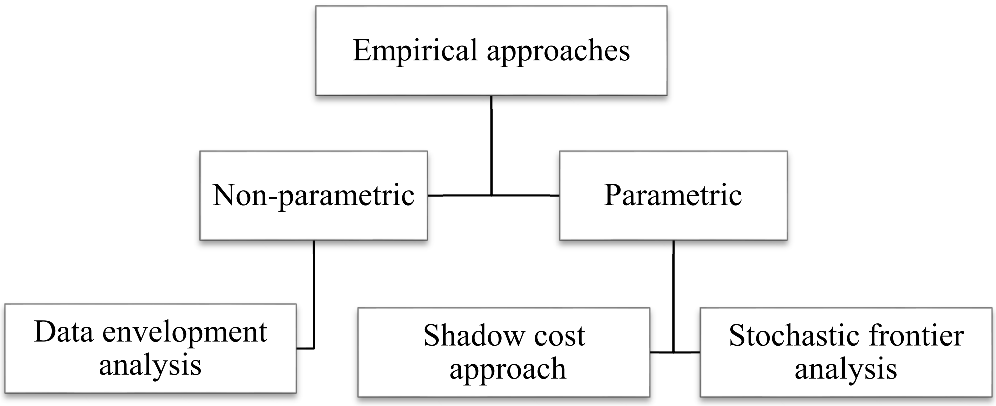
Source: Adopted from Worthington (2004).

3.2 Static efficiency

3.2.1 Non-parametric and parametric methods

Based on the theoretical background to measure efficiency (cf. section 3.1), several methods are available to analyze efficiency. These methods can be grouped as non-parametric and parametric methods (Figure 11). The distinction is mainly based on how the frontier is defined: via a parametric function using an econometric model or non-parametrically using linear programming.

Figure 11. Empirical methods to analyze efficiency



A prominent example for non-parametric methods is the DEA that originates in the work of Farrell (1957) and has gained considerable attention by the work of Charnes et al. (1978). Essentially, DEA uses linear programming techniques to construct a piecewise surface over the data and calculates efficiency relative to this surface (Mendes et al. 2013). Any firm that lies beneath the surface is assumed to be inefficient. Using the DEA approach, technical efficiency scores can be computed by solving the following optimization problem for each firm where the firm under consideration is indicated by '0' (Cantner et al. 2007; Coelli et al. 2005)

$$\min_{\varphi,\pi} \varphi \tag{4}$$

subject to

$$-y_{q0} + \sum_{i=1}^{\bar{i}} \pi_i y_{qi} \geq 0, \qquad q = 1,...,\bar{q}$$

$$\varphi x_{n0} - \sum_{i=1}^{\bar{i}} \pi_i x_{ni} \geq 0, \qquad n = 1,...,\bar{n}$$

where $\overline{n}$ represents the number of variable input factors and $\overline{q}$ denotes the number of outputs with $\pi_i \geq 0$, $x_{ni} \geq 0$, $y_{qi} \geq 0$, $q = 1,...,\overline{\mathrm{q}}$, $n = 1,...,\overline{\mathrm{n}}$ and $i = 1,...,\overline{\mathrm{i}}$. Symbol φ denotes to which level all inputs could be reduced proportionally and hence indicates the technical efficiency of the i^{th} firm computed by the DEA model. Symbol π_i denotes weighting factors. The first constraint is related to the output use and the second to the input use. If input prices (w) are available, the solution of the following cost minimization DEA

$$C_{\min,0} = \min_{\pi, x_{n0}} \sum_{n=1}^{\overline{n}} w_{n0} x_{n0}^{*} \tag{5}$$

subject to

$$-y_{q0} + \sum_{i=1}^{\overline{i}} \pi_i y_{qi} \geq 0, \qquad q = 1,...,\overline{\mathrm{q}}$$
$$x_{n0}^{*} - \sum_{i=1}^{\overline{i}} \pi_i x_{ni} \geq 0, \qquad n = 1,...,\overline{\mathrm{n}}$$

results in the cost-minimizing input quantity of the firm under consideration, x_{n0}^{*}. Using this quantity, the firms' economic efficiency can be calculated by $\mathrm{EE_o} = \sum_{n=1}^{\overline{n}} w_{n0} x_{n0}^{*} \Big/ \sum_{n=1}^{\overline{n}} w_{n0} x_{n0}$.

An advantage of DEA is that many inputs and many outputs can be included simultaneously. However, the efficiency scores may increase if the number of inputs increases (Silva et al. 2004). Furthermore, DEA does not require a specific functional form of the production function to construct the surface and hence DEA might be easier to perform (Cantner et al. 2007; Mendes et al. 2013). In addition, Sharma et al. (1997) state that DEA results are more robust than those obtained from parametric approaches. The static DEA framework has been widely applied to agriculture for example by Thiele and Brodersen (1999), Silva et al. (2004), Oude Lansink et al. (2002) and Barnes et al. (2011). Further international applications can be found in Reig-Martinez and Picazo-Tadeo (2004) for citrus farming in Spain and in Yusuf and Malomo (2007) for poultry egg production in Nigeria.

The classical DEA is non-stochastic, consolidating noise and inefficiency (Reinhard 1999; Mendes et al. 2013) which leads to a drawback in the classical deterministic DEA model: all deviations from the frontier are related to inefficiency. This shortcoming is overcome by the stochastic frontier analysis (SFA)—dating back to Meeusen and van den Broeck (1977) and Aigner et al. (1977)—which is an econometric approach, being stochastic and distinguishes the effects of noise from the effects of inefficiency (Fried et al. 2008). Essentially, deviations from the frontier might not be completely controlled by the firm (Reinhard 1999) and, hence, a component is added to the deterministic specification capturing unexplained, random deviations from the frontier. The stochastic frontier model according to Aigner et al. (1977) can be written as

$$y = f\left(x;\zeta\right) + \varepsilon \tag{6}$$

where y is output and x is a vector of inputs, ζ 's are parameters to be estimated. The error term ε is decomposed into two terms u and v . u is an identically distributed one-sided error term and captures inefficiency in production and v is an identically distributed two-sided error term and stands for random noise (Reinhard 1999). Accordingly, deviations from the frontier are not solely caused by inefficiency but also by random fluctuations—resulting from external effects on the production process or possible measurement errors (Coelli et al. 2005). In contrast to DEA, in SFA a specific functional form for the production function—e.g., Cobb-Douglas or translog—has to be imposed. Hence, the estimated frontier parameters and the efficiency levels are conditional on the chosen functional form. Thus, selecting an appropriate functional form is the core of the parametric approach. Alike the DEA framework, SFA has been widely applied to the agricultural sector to measure efficiency, e.g., Kumbhakar et al. (1989), Bravo-Ureta and Rieger (1991), Battese and Coelli (1995), Maietta (2008) or Lakner (2009). In comparison, the stochastic non-parametric envelopment of data (StoNED) can be seen as a semi-parametric approach and combines the idea of DEA and SFA models by merging the non-parametric piece-wise linear frontier (DEA) with decomposing residuals into noise and inefficiency (SFA). Compared to DEA, the StoNED approach is more robust to data errors since all observations influence the frontier and not only the efficient ones (Johnson and Kuosmanen 2012; Kuosmanen and Kuosmanen 2009; Kuosmanen and Kortelainen 2012).

An alternative approach for the efficiency estimation is the parametric shadow cost approach. It was first proposed by Lau and Yotopoulos (1971) under a profit maximization assumption and later formulated by Toda (1976) in a cost minimization framework. The approach enables the researcher to decompose economic efficiency into its technical and allocative component and is less cumbersome than the SFA approach (Kumbhakar and Lovell 2000). Within the shadow cost approach, efficiency is modeled by additional parameters, which are introduced and estimated in contrast to modeling efficiency through an error component (Kumbhakar and Lovell 2000). The basic idea is that a firm minimizes its shadow costs instead of its observed costs. The shadow prices are defined as input prices that force the technical efficient input use to be the cost-minimizing one (Kumbhakar and Lovell 2000; Blank and Eggink 2004). In the presence of allocative inefficiency, shadow and observed prices will differ (Kumbhakar and Lovell 2000). Since the shadow prices itself are not observable, it is not possible to directly estimate the shadow cost function. Technical inefficiency is introduced by either scaling the input vector—denoted as input orientation—or by scaling the output vector—denoted as output orientation. The emphasis in this section is on input orientation since the applied model (cf. section 4) is based on an input-oriented[7] measure of efficiency—a reasonable assumption for dairy farms operating under the milk quota system (Sauer and Latacz-Lohmann 2014) and dairy farm managers may have more control over inputs, while outputs are mainly defined by demand and limited by resources and capacity (Kapelko and Oude Lansink 2013).

The input-oriented measurement of efficiency using the shadow cost approach is presented in Figure 12 for a firm using two inputs x_1 and x_2 to produce the output y. The isoquant *SS'* denotes the minimum combination of inputs that are necessary to produce the output (cf. section 3.1). The input-oriented measure of technical efficiency is denoted by $0 < (1/\tau) \leq 1$, with $\tau \geq 1$ denoting technical inefficiency (Kumbhakar and Lovell 2000), and measures the degree by which the observed input use departs from the optimal use (Atkinson and Cornwell 1994). A firm operating at x is technically inefficient and could reduce its inputs to x^b and still produce the same level of output. Furthermore, the firm operates allocative inefficient if the marginal rate of substitution at x^b diverges from the observed input price relation, w_1/w_2. Instead, a firm producing at x^E would be cost—technically and allocatively—efficient, the firm is on the isoquant and the input ratio is optimal according to observed prices—the marginal rate of substitution is equal to the observed price relation (Reinhard and Thijssen 2000). In contrast, a firm producing at x^b is technically efficient, but not allocative efficient since the marginal rate of substitution is not equal to the observed prices. However, the firm is allocative efficient with respect to the shadow prices given by $w_{12}^b = \lambda_{12}(w_1/w_2)$. Therein λ_{12} is interpreted in terms of an over- or underuse of the resources, where $\lambda_{12} < 1$ indicates that input x_1 is overused in relation to x_2 (Kumbhakar and Lovell 2000).[8]

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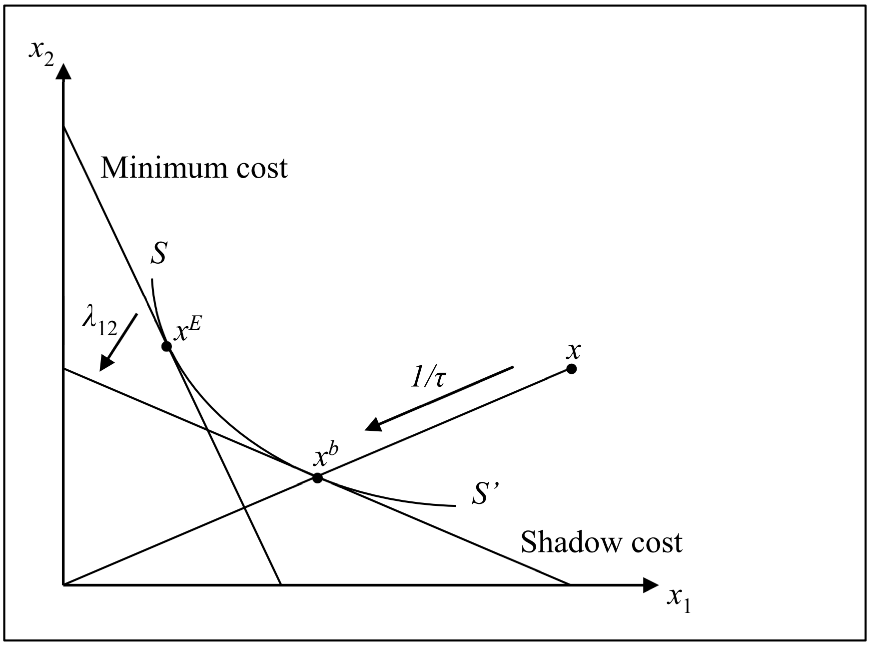
7 A detailed description of the shadow cost approach using output orientation is given by Kumbhakar and Lovell (2000).

8 The shadow cost model in its static form will not be further described in detail here. The steps important to consider are in detail described in section 4 where the dynamic efficiency model used in this thesis and its derivation procedure is explained.

Figure 12. Shadow cost approach



Source: Adopted from Kumbhakar and Lovell (2000).

The shadow cost approach has been applied to various sectors to measure and decompose economic efficiency. The following literature overview highlights the recent research concentrating on used data and obtained results. Toda (1976) uses data on manufacturing industries and shows that the unobserved (shadow) relation between wage and rental differs from the observed ratio—giving a hint to factor price disparity. In addition, the author estimates total factor productivity and states that the total factor productivity growth is higher if shadow prices instead of observed prices are used within the calculation. Eight years later, Atkinson and Halvorsen (1984) use the approach by Toda (1976) to estimate relative efficiency of private U.S. electricity companies and elaborate on the effect on cost and input demand. The results point out that relative price inefficiency leads to an increase of cost by 3.8%. As a result of inefficiency the demand for capital and labor increases by 18.8% and 3.5%, respectively.

Extending their former study, Atkinson and Halvorsen (1986) estimate relative efficiency of privately and publicly owned electricity companies based on the shadow cost approach and aim at investigating whether ownership affects efficiency. Their analysis is based on 123 regulated privately and 30 publicly owned companies and points out that the companies are equally efficient. However, the authors state that this does not imply absolute cost efficiency. In addition, inefficiency results in higher demand for capital and labor and in higher production cost. Targeting ownership effects, Bhattacharyya et al. (1994) explore the relative efficiency of U.S. water utilities. Their empirical analysis is based on data of 32 privately and 225 publicly owned water utilities. Similar to Atkinson and Halvorsen (1984), unobserved shadow prices reflect the influence of regulation constraints on water utilities. Bhattacharyya et al. (1994) state that publicly owned companies are on average more efficient than their private counterparts even though these firms have a more dispersed technical inefficiency. With respect to allocative efficiency, the results highlight an overuse of labor and an underuse of energy compared to material for both groups of water utilities.

Focusing on U.S. airlines, Atkinson and Cornwell (1994; 1998) use the shadow cost approach to estimate technical and allocative efficiency. Atkinson and Cornwell (1994) show that firm-specific technical and allocative efficiencies can be estimated using a translog cost function and that cost savings of about 50% would result from an efficient production. These authors stress the importance of assuming input or output orientation since this could influence the resulting efficiency scores. Atkinson and Cornwell (1998) develop two models to estimate firm-specific technical and allocative efficiencies: a model based on profit maximization and a model based on cost minimization. These authors show that computational problems arise while estimating the profit function and the related input demand shares. Hence, Atkinson and Cornwell (1998) use the cost minimization model to estimate technical inefficiency of U.S. airlines. The inefficiency amounts to 0.45 and capital is overused in relation to materials.

The efficiency of hospitals is analyzed by Eakin and Kniesner (1988) and Blank and Eggink (2004). Eakin and Kniesner (1988) use a translog cost function to analyze allocative efficiency and report that U.S. hospitals overuse capital. Due to allocative inefficiency costs increase by 4%. Blank and Eggink (2004) analyze technical and allocative efficiency of Dutch hospitals. Shadow prices and hence price distortion parameters are defined separately for each personnel group. The results state that the average technical efficiency amounts to 0.86 and allocative efficiency amounts to 0.92. Other personnel and nursing personnel is overused compared to materials. Hence, the hospitals could reduce their costs by 8% by reallocating the resources.

The shadow cost approach has been widely applied in the agricultural sector for measuring and decomposing economic efficiency. A first application dates back to Lau and Yotopoulos (1971) to measure relative efficiency of farms in India and to compare the efficiency scores among groups. These authors state that the hypothesis of equal efficiency between the small farms—with less than 10 acres of agricultural land—and large farms is rejected and that small farms are found to be more efficient. Sidhu (1974) analyzes the relative efficiency of wheat production in India and the results point out that farmers who own a tractor are not better off than farmers without own tractor. These author found that smaller farms—with less than 10 hectares of agricultural land—are as efficient as larger farms. Based on data for 436 Pakistani farms, Ali et al. (1996) report that small farms are more efficient and that inefficiency further depends on education and credit access. In addition, these authors found a suboptimal use of fertilizer and labor and conclude that higher education and advisory services in addition to an improved availability of credits might reduce the difference in efficiency between more and less efficient farms. Balint and Sauer (2008) also discover different factors that affect efficiency levels and use the shadow cost approach to estimate allocative and group-specific technical efficiency for Romanian maize producers. The empirical results show a high technical efficiency of small-scale farmers in contrast to low allocative efficiency. Technical efficiency is positively related to agricultural training on the farm level and negatively related to the use of insecticides and herbicides.

Recently, Roll (2013) has used the shadow cost approach for measuring the performance of Norwegian salmon farms. The empirical results show that the farms are on average 0.98 technical efficient and that labor is overused relative to feed. In addition, cost reductions of 50% are observed over the sample period—mainly due to reduced allocative inefficiency and technological progress. Even though labor is overused relative to feed, the overuse decreased over time. Futhermore, the shadow cost approach is used to measure economic efficiency of dairy farms, e.g., by Maietta (2000), Reinhard and Thijssen (2000) and Mosheim and Lovell (2009) (cf. section 2.3).

3.2.2 Consideration of uncertainty

The agricultural sector is faced with uncertainty introduced either by unpredictable and uncontrollable characteristics of the physical environment—e.g., lack of rainfall and natural disasters—or by market instability (O'Donnell and Griffiths 2006; Serra et al. 2014; Skevas et al. 2014). Ignoring these aspects may lead to biased efficiency estimates (e.g., Chen and van Dalen 2010). The effect of uncertainty on agricultural production decisions and on efficiency has been analyzed in the static efficiency literature using theoretical modeling approaches and empirical studies. Different approaches were utilized to account for uncertainty while estimating firms' efficiency—e.g., SFA, DEA and state-contingent models.

Kumbhakar (1993) was the first authors to take up this issue in static efficiency analysis extending the Aigner et al. (1977) stochastic production frontier model (cf. equation (6)) by incorporating an additional function. Accordingly, the production process is characterized by

$$y = f(x;\zeta)e^{g(x;\xi)\varepsilon} \tag{7}$$

where y denotes output, x denotes a vector of inputs and $f(x;\zeta)$ represents the deterministic part of the production function. Production uncertainty enters the production function multiplicatively and is captured by $e^{g(x;\xi)\varepsilon}$ and ζ and ξ denote unknown parameters to be estimated. The error term ε is specified by Kumbhakar in a panel data setting as $\varepsilon_{it} = u_i + \kappa_t + v_{it}$ where i represents individuals with $i = 1,...,\overline{i}$, t indexes time ($t = 1,\ldots,T$) and u_i is interpreted as technical inefficiency, κ_t as time-specific effects and v_{it} captures random noise. In his empirical application for dairy farms in Sweden from 1986–1988, Kumbhakar uses one output—total income from dairy activities—and six inputs—feed concentrates, material, labor, capital, grass fodder and pasture land. u_i and κ_t are estimated using firm and time dummies and technical efficiency is recalculated from the estimated coefficients of the firm dummies: Swedish dairy farms have an average technical efficiency of 0.928. Furthermore, marginal effects for the farms—given by the change in the variance of y induced by input changes, $\partial V(y)/\partial x_i$ —are calculated and negative marginal effects were observed for material, grass fodder and pasture use indicating that output variance decrease with using more material, grass fodder and pasture land. In contrast, output variance increases with increasing use of capital, labor and feed concentrates.

Kumbhakar (2002) extends his former study by deriving a model that includes production risk and producers' attitude toward risk. Kumbhakar uses two model specifications: the additive and the multiplicative form. The two models are given by

$$y = f(x,K) + g(x,K)\left[v_{\sigma^2} - u\right] \tag{8}$$

and

$$y = f(x,K)e^{(-u)} + g(x,K)v_{\sigma^2} \tag{9}$$

where x denotes a vector of inputs, K is a vector of quasi-fixed inputs, v_{σ^2} denotes an error term representing production uncertainty and u is interpreted as technical inefficiency. The production function is decomposed into a mean production function $f(x,K)$ and a production risk function $g(x,K)$. In the additive model (cf. equation (8)) inefficiency is attached to the production risk function. In contrast, in the multiplicative model (cf. equation (9)) technical inefficiency is introduced in the mean production function by $f\left(x,K\right)e^{(-u)}$ as in Aigner et al. (1977). Kumbhakar (2002) assumes producers that maximize expected utility of profit and the first-order conditions of this problem, used to introduce risk preferences, are given by

$$f_n\left(x,K\right)=w_n-\theta\cdot g_n\left(x,K\right)+\upsilon\cdot g_n\left(x,K\right)+\eta_n \tag{10}$$

and

$$f_n\left(x,K\right)\cdot\left(1-\upsilon\right)=w_n-\theta\cdot g_n\left(x,K\right)+\eta_n \tag{11}$$

for the additive and multiplicative model, respectively. $f_n\left(x,K\right)=\partial f\left(x,K\right)/\partial x_n$ can be interpreted as the change in mean output for a unit change in the variable input. Furthermore, $g_n\left(x,K\right)=\partial g\left(x,K\right)/\partial x_n$ and the variable inputs are risk-increasing (risk-decreasing) if $g_n\left(x,K\right)$ is positive (negative). The factor price for variable inputs is given by w and η_n is an error term representing allocative efficiency of the n^{th} variable factor. The risk preference functions, θ and υ, capture the producers' risk preferences. Compared to equation (10), in equation (11) the risk preferences associated with production uncertainty and technical inefficiency are not additive. Furthermore, equations (10) and (11) highlight that technical inefficiency as well as production risk might affect input demand. Essentially, the embedded risk preference functions include, among others, measures for risk aversion where the respective signs give a hint whether producers are risk averse, risk neutral, or risk seeker. Using data on Norwegian salmon farms, Kumbhakar (2002) specifies two quasi-fixed inputs—feed and capital—and one variable input—labor—for estimating equations (10) and (11). The results indicate that Norwegian salmon farmers are risk averse and production risk increases with feed usage and decreases with labor and capital use. The farms show an average technical inefficiency of 0.08. The model proposed by Kumbhakar (2002) has been applied by Bokusheva and Hockmann (2006) to examine production risk and technical inefficiency in Russian agriculture. Alternative specifications to address production risk have been investigated by Battese et al. (1997) or Wang (2002).

An alternative approach for analyzing inefficiency and uncertainty is the state-contingent approach. In contrast to conventional stochastic frontier models these models take into account that output is conditional on the state of nature representing a particular uncertain event. This idea originally dates back to Arrow and Debreu (1954) and theoretical contributions are given by Chambers and Quiggin (2000; 2002). Essentially, for each state of nature there exists a state-contingent production function. Hence, uncertainty is represented by differentiating outputs according to the state of nature in which these outputs are produced (Serra et al. 2014). According to Chambers and Quiggin (2000), these states might range from “very poor seasonal conditions” to “excellent seasonal conditions” and are the elements of a set corresponding to combinations of rainfall, temperature and humidity. These authors illustrate that through a different input factor allocation depending on different states of nature the farms can cope with uncertainty.

Applications of the state-contingent approach are given for instance by O’Donnell and Griffiths (2006), Chavas (2008), O’Donnell et al. (2010) and Nauges et al. (2011). O’Donnell and Griffiths (2006) state that empirical applications are cumbersome since the different states of natures have to be quantified. Their results for Philippine rice farmers demonstrate that higher technical efficiency estimates are obtained if a state-contingent framework instead of a stochastic frontier model is used because deviations from the frontier due to risk were misinterpreted as inefficiency. This is in line with O’Donnell et al. (2010) who highlight that SFA and DEA may produce inaccurate efficiency measures if production decisions are contingent on the state of nature. Extending the theoretical model of O’Donnell et al. (2010), Nauges et al. (2011) analyze production under uncertainty and inefficiency for farms in Finland. Uncertainty is considered using three states of nature defined in terms of favorable states for wheat, barley and oat. The results show that technical efficiency amounts to 0.63 and that efficiency will be lower in unfavorable states of nature. Furthermore, Nauges et al. (2011) point out that producers with a state-allocable production may have the ability to handle production risk more actively. The state-contingent approaches provide insights that if producers act under uncertain environmental conditions, conventional models may lead to biased estimates and hence to an inaccurate measure of technical efficiency. Recently, Serra et al. (2014) have used the state-contingent approach to measure technical efficiency for a sample of Catalan arable crop farms.

Several authors attempted to incorporate uncertainty into the measurement approach of static efficiency using DEA. One idea is to use upper and lower bounds of cost efficiency to account for uncertain prices and incomplete price information (e.g., Camanho and Dyson 2005; Toloo and Ertay 2014; Fang and Li 2012). Essentially, this is done by incorporating the available price information as additional weight restrictions to equation (5). Hence, based on this approach, cost efficiency is measured in the light of the most and less favorable price scenario using a pessimistic and an optimistic DEA model (Camanho and Dyson 2005). An alternative idea—

presented by Chambers et al. (2011)—uses an event-specific DEA model to incorporate climatic variables as a source of uncertainty. By using western Australian barley production data, these authors show that efficiency scores change when uncertainty is not considered. Skevas et al. (2014) use a DEA where output variance is incorporated as undesirable output. By applying the model to Dutch arable farm data from 2003–2007, these authors show that inefficiency scores differ between risk-reducing inputs such as fungicides and other variable inputs such as energy (0.07 versus 0.04).

However, the aforementioned static efficiency studies do not allow the researcher to distinguish between variable and quasi-fixed production factors. For both inputs it is assumed that these can be adjusted instantaneously without costs. The time component of farm-level decision making—namely the time interdependence of production decisions—is particularly important if quasi-fixed factors are adjusted, and is not considered in static efficiency analysis. A special attribute of quasi-fixed inputs is that additional costs occur with the adjustment and hence an instantaneous adjustment to the optimal level is either not possible or not reasonable (Nemoto and Goto 1999). These issues are taken into account in the dynamic efficiency measurement.

3.3 Dynamic efficiency

3.3.1 Non-parametric and parametric methods

Analyzing efficiency within a dynamic framework—which accounts for the time interdependence of production decisions and the existence of adjustment cost when changing the fixed factors—has recently become a well-established approach. Dynamic efficiency approaches can be classified—similar to static efficiency approaches—into non-parametric and parametric approaches, however, non-parametric approaches have been used more frequently. The literature related to non-parametric settings will be reviewed briefly since the applied model is based on a parametric approach.

Nemoto and Goto (1999; 2003) develope a non-parametric DEA model that incorporates adjustment costs of investment in terms of forgone output; that is, the authors extend DEA to a dynamic framework. These authors state that the static optimization might results in biased inefficiency measurements if quasi-fixed inputs exist in the production process. To measure foregone output, Nemoto and Goto (1999) consider the quasi-fixed inputs at the end of the period as output. This idea introduces a further constraint to the static DEA problem in equation (5). In addition, the objective function is extended by incorporating quasi-fixed factors and their respective prices introducing the quasi-fixed factor constraint to the optimization problem. A first application was performed by Nemoto and Goto (2003) for Japanese electric utilities where the data cover the years 1981 to 1995. The authors estimate cost efficiency and decompose it into a static and a dynamic component. Their results provide empirical evidence for the need to consider the quasi-fixed character of production factors: variable inputs are used efficiently; hence, inefficiency originates from adjusting the quasi-fixed inputs. Svetlov and Hockmann (2009) apply this approach to the agricultural sector. These authors analyze the relation between farm size and efficiency for corporate farms in Russia between 1996 and 2004 and provide empirical evidence for a positive correlation between farm size and efficiency. The average economic efficiency of corporate farms in Moscow oblast amounts to 0.50.

Skevas et al. (2012) present a notable attempt to measure technical efficiency in the presence of uncertainty for Dutch arable farms using a dynamic DEA model. Essentially, after calculating the efficiency scores, these scores are adjusted to account for the effect of different climatic conditions. For this, these authors incorporate weather related variables and their standard deviation into the equation for the adjusted efficiency scores. Following that, the adjusted and the un-adjusted scores are compared. The results state that inefficiency decreases when production uncertainty is considered—0.18 vs. 0.04. Accordingly, adjusting the efficiency scores for farms in an uncertain environment results in improved measures for efficiency. However, these authors do not consider price uncertainty.

Silva and Stefanou (2003; 2007) use a non-parametric revealed preference approach and develop measures of technical, allocative and economic efficiency in the short run and in the long run starting from dynamic cost minimization. Using data of 61 Pennsylvanian dairy farms from 1986 to 1992, these authors find that inefficiency is mainly caused by a failure in adjusting the quasi-fixed factors capital and labor. Oude Lansink and Silva (2006) built upon the framework of Silva and Stefanou (2003) and measure dynamic efficiency of 89 Dutch horticulture firms using a directional distance function. Their results indicate that short-run technical efficiency is similar to long-run technical efficiency and amounts to 0.71. In addition, these authors found that allocative efficiency of Dutch horticulture firms is higher in the short run indicating that variable factors are allocated more optimal compared to quasi-fixed factors such as buildings and land. This is caused by a sluggish adjustment of quasi-fixed factors. Sluggish behavior thereby describes that this adjustment is not achieved instantaneously but stepwise due to the presence of adjustment costs. Recently, Silva and Oude Lansink (2012) have measured dynamic efficiency of Dutch glasshouse horticulture firms and Kapelko et al.

(2012) have estimated dynamic efficiency of Spanish construction firms using a directional distance function. A detailed summary of non-parametric models for dynamic efficiency measurement is given by Fallah-Fini et al. (2014).

An emerging body of research is performed using parametric approaches, which can be further distinguished between reduced-form and structural models. A number of reduced-form models have been applied; however, structural models have become more popular in recent years. In reduced-form models no mathematical representation of the firms' dynamic behavior is defined. Applications are given for instance by Ahn et al. (2000), Tsionas (2006) and Emvalomatis et al. (2011). The temporal behavior of inefficiency is addressed by using an autoregressive specification for the firm-specific inefficiency measures in the dynamic stochastic frontier models. Ahn et al. (2000) and Tsionas (2006) state that inefficiency is autocorrelated for U.S. airlines and commercial banks, respectively. Emvalomatis et al. (2011) extend a stochastic distance function by autocorrelated inefficiency and found that inefficiency persists over time for German and Dutch dairy farms (cf. section 2.3).

In structural dynamic efficiency models, the optimization behavior of a firm—subject to dynamic constraints, such as the equation of motion—is explicitly defined. Structural efficiency models are proposed for instance by Serra et al. (2011), Rungsuriyawiboon and Stefanou (2007) and Rungsuriyawiboon and Hockmann (2012). Serra et al. (2011) use a directional distance function to estimate technical and allocative efficiency on the farm-level. Their application is performed for a sample of specialized dairy farms in the Netherlands (cf. section 2.3). Rungsuriyawiboon and Stefanou (2007) develop a parametric dynamic efficiency model by integrating the static shadow cost approach (cf. section 3.2) into the dynamic dual[9] model of intertemporal decision making. The shadow cost approach is used to achieve the decomposition of economic efficiency and a dynamic dual model is employed since duality theory offers the advantage that the procedure results in factor demand equations that are consistent with the optimization behavior of the firm. By using this theory, intertemporal optimization problems are solved based on the value function being the central element of dynamic duality (Howard and Shumway 1988; Rungsuriyawiboon 2003). The model of Rungsuriyawiboon and Stefanou

[9] Dynamic duality has been used to develop and estimate dynamic factor demand equations, e.g., for U.S. agriculture by Luh and Stefanou (1991; 1993), Taylor and Monson (1985) and Vasavada and Chambers (1986). Howard and Shumway (1988) use the dynamic dual approach to examine the dynamic structure of the U.S. dairy industry and estimate adjustment rates for quasi-fixed inputs. Chang and Stefanou (1988) use the dynamic duality approach to estimate separate adjustment rates for expansion and contraction phases for quasi-fixed factors for Pennsylvania dairy farms.

(2007) is the basis for deriving a dynamic efficiency model under uncertainty and is hence presented in greater detail.

In their model, Rungsuriyawiboon and Stefanou (2007) assume that a firm minimizes its discounted sum of future production costs over an infinite horizon subject to the production sequence and the equation of motion of capital. The cost minimization problem is expressed in terms of the value function $J(\cdot)$ given by

$$J\left(w(0),c(0),y(0),K(0)\right)=\min_{x,I} E_0\int_0^{\infty} e^{-rt}\left[\sum_n\left(w_n(t)\cdot x_n(t)\right)+\sum_m\left(c_m(t)\cdot K_m(t)\right)\right]\cdot dt \tag{12}$$

where t denotes time,[10] E_0 is the expectation operator conditional on information available at present time, and $x_n(t)$ symbolizes the n^{th} variable factor, with $\left[x_1(t),\dots,x_{\bar{n}}(t)\right]\in\Re_{+}^{\bar{n}}$ and $\left[w_1(t),\dots,w_{\bar{n}}(t)\right]\in\Re_{++}^{\bar{n}}$ represent the respective factor prices with $n=1,\dots,\bar{n}$. Symbol $K_m(t)$ denotes the m^{th} quasi-fixed input level with $\left[K_1(t),\dots,K_{\bar{m}}(t)\right]\in\Re_{+}^{\bar{m}}$ with $m=1,\dots,\bar{m}$ and the respective factor prices are given by $\left[c_1(t),\dots,c_{\bar{m}}(t)\right]\in\Re_{++}^{\bar{m}}$. $I_m(t)$ symbolizes gross investment in the m^{th} quasi-fixed factor and r is a constant discount rate. The value function represents the long-run cost function starting at time t (Stefanou 1989; Rungsuriyawiboon and Stefanou 2007).

The optimization problem presented by Rungsuriyawiboon and Stefanou (2007) is subject to the production sequence and equation of motion for the stock of quasi-fixed inputs. The production sequence constraint is given by

$$y(t)\leq F\left(x(t),K(t),\dot{K}(t)\right) \tag{13}$$

wherein the firm produces a single output y. $F\left(x(t),K(t),\dot{K}(t)\right)$ denotes the production relationship representing the firm's technology and is a function of a vector of variable factors selected in the short run, $x(t)$, a vector of quasi-fixed inputs, $K(t)$, and the change in the quasi-fixed factor level, $\dot{K}(t)$, denoted as net investment. If a firm adjusts its quasi-fixed factors this will—in contrast to adjusting variable factors—not be without a penalty in addition to the acquisition costs. These costs can be classified as external or internal (Stefanou 1989).

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[10] The subscripts t (time dependency) and i (individuals) are suppressed wherever possible.

External costs capture that it might be cheaper to under- or overutilize quasi-fixed resources instead of renting the factors and this might occur for example due to market forces (Brechling 1975).

In contrast, internal costs are associated with the adjustment of the technological production relationship and can be explained in terms of forgone output since the investment requires resources that could have been used otherwise for producing output (Stefanou 1989). External costs are added to the firm's other costs whereas internal adjustment costs may interact with the production factors (Brechling 1975). Including $\dot{K}(t)$ as an argument of the production function takes these internal costs into account (Rungsuriyawiboon and Stefanou 2007). The production function is assumed to be concave in $\dot{K}_m$ which implies increasing marginal cost of adjustment (Stefanou 1989; Rungsuriyawiboon and Stefanou 2007): the speed of the change in the capital stock defines the size of the output loss. That is, the loss is larger for faster adjustments. Hence, a firm will lean towards a more slowly adjustment of the capital stock such that $\dot{K}_m F_{\dot{K}_m} < 0$ and $F_{\dot{K}_m \dot{K}_m} < 0$ holds (Stefanou 1989; Rungsuriyawiboon and Stefanou 2007), subscripts of F indicate partial differentiation. $\dot{K}_m F_{\dot{K}_m} < 0$ indicates that the marginal product of $\dot{K}_m$ ($F_{\dot{K}_m}$) will be more negative if $\dot{K}_m$ is higher; that is, output decreases with an expansion of the quasi-fixed factor stocks. Further, $F_{\dot{K}_m \dot{K}_m} < 0$ describes that the decrease in the output level—the marginal cost of adjustment in physical terms—is higher for larger levels of $\dot{K}_m$ (Rungsuriyawiboon and Stefanou 2007). This captures the sluggish or gradual behavior in adjusting the levels of quasi-fixed factors (Rungsuriyawiboon 2003).

The second constraint presented by Rungsuriyawiboon and Stefanou (2007) is given by

$$\dot{K}_m(t) = \left(I_m(t) - \delta \cdot K_m(t)\right) \tag{14}$$

with $K(0) = K_0 > 0$, $K_m(t) > 0$ and δ denotes a constant depreciation rate. Equation (14) expresses the development of the quasi-fixed input stock and it states that a change in the capital stock equals gross investment minus depreciation. A given initial endowment is assumed by $K(0) = K_0 > 0$ stating that the state variable starts at a given value K_0. Hence, the equation of motion describes how the planned choice of the control variable will drive the state variable over time. The levels of the control variable can be decided by the decision maker; that is, the state variable K is determined by the choice of control variables (Christiaans 2004). In addition, the value of the state variable must be positive at each point in time ($K_m(t) > 0$).

The optimization problem as given in equations (12)–(14) is solved by Rungsuriyawiboon and Stefanou (2007) using dynamic programming and the Hamilton-Jacobi-Bellman (HJB) equation for this problem is given by

$$\begin{aligned} rJ\left(\mathrm{w},\mathrm{c},\mathrm{y},K\right) = \min_{x,I} \Bigg\{ & \sum_n \left(w_n \cdot x_n\left(t\right)\right) + \sum_m \left(c_m \cdot K_m\left(t\right)\right) + \sum_m \left(J_{K_m} \cdot \left(I_m\left(t\right) - \delta \cdot K_m\left(t\right)\right)\right) \\ & + \gamma\left(t\right) \cdot \left[y\left(t\right) - F\left(x_n\left(t\right), K_m\left(t\right), \dot{K}_m\left(t\right)\right)\right] \Bigg\} \end{aligned} \tag{15}$$

where subscripts of J indicate partial differentiation: $J_{K_m} = \partial J / \partial K_m$ represents the partial derivative of J with respect to the m^{th} quasi-fixed factor and accounts for a change in the value function if the fixed factor level changes. $\gamma\left(t\right) = \partial J / \partial y$ is the co-state variable associated with the production target constraint and represents short-run marginal cost (Stefanou 1989; Rungsuriyawiboon and Stefanou 2007). Based on this, Rungsuriyawiboon and Stefanou (2007; 2008) apply the shadow cost approach and derive dynamic factor demand functions for variable and quasi-fixed inputs. Cost efficiency is decomposed into technical and allocative inefficiency with regards to the variable factors and quasi-fixed factors, respectively.[11] The main idea is that the observable prices differ by an allocative inefficiency term from the shadow prices. Accordingly, the shadow input prices are defined as those prices that force a technically efficient input vector to be the cost-minimizing choice with regards to the shadow prices, that is, the optimality relationship. Based on this distinction, Rungsuriyawiboon and Stefanou (2007) set up two types of cost frontiers and their corresponding value functions to measure technical inefficiency: the shadow value function and its counterpart in terms of observables. The shadow value function is constructed to guarantee the optimality relationship, that is, the technically efficient input use is supposed to be the shadow cost-minimizing one. In the presence of perfect (allocative and technical) efficiency, the value function in terms of observables is equivalent to the shadow value function. In the presence of inefficiency these functions differ. Consequently, these authors define measures for technical inefficiency as the

[11] All measures are defined as input-oriented measures.

differences between the demand levels based upon the shadow value function and the optimal levels based upon the value function in terms of observables.[12]

Rungsuriyawiboon and Stefanou (2007; 2008) suggest a quadratic functional form for the value function to attain estimable factor demand functions. In line with the data and to facilitate the estimation, these authors assume technical efficiency of quasi-fixed factors to be unity and follow Cornwell et al. (1990) for producer-specific and time-varying allocative and technical efficiency scores. The empirical results for U.S. electricity companies indicate an average technical efficiency of variable inputs of 0.77 and an overuse of net investment as well as a relative underuse of the variable production factors. In addition, the adjustment rate of capital amounts to 0.03 implying that the capital stock adjusts 3% per year to the long-run optimal value. Though these authors derive investment and variable input demand functions along with efficiency parameters, these authors assume that the decision maker expects current prices and technology to persist indefinitely in the future; that is, static expectations are assumed.

Rungsuriyawiboon and Hockmann (2012) extend the model by Rungsuriyawiboon and Stefanou (2007) for the multiple quasi-fixed factor case to investigate structural change and technical change in Polish agriculture. Following the procedure in Rungsuriyawiboon and Stefanou (2007), these authors obtain demand functions for quasi-fixed factors and variable inputs. To ease the derivation and the empirical setup the two quasi-fixed factors—capital and land—are assumed to be independent. Rungsuriyawiboon and Hockmann (2012) estimate average technical efficiency scores of net investment and variable factors equal to 0.54 and 0.58, respectively, and average allocative efficiencies of net investments in capital and land equal to 0.53 and 0.75. These scores are found to be stable over time and among farm specializations. The results further indicate that the quasi-fixed factor adjustment of Polish farms is rather sluggish: the adjustment rate for capital and land amount to 0.037 and 0.034 per annum, respectively, implying 27 and 30 years to adjust to the optimal levels. However, their approach does not consider price uncertainty.

3.3.2 Efficiency and adjustment over time

This section aims at elaborating on the relation between efficiency and the adjustment process over time when quasi-fixed factors are present. Essentially, a firm seeks to explore the optimal amount of production inputs in a given time period. However, not all production inputs are

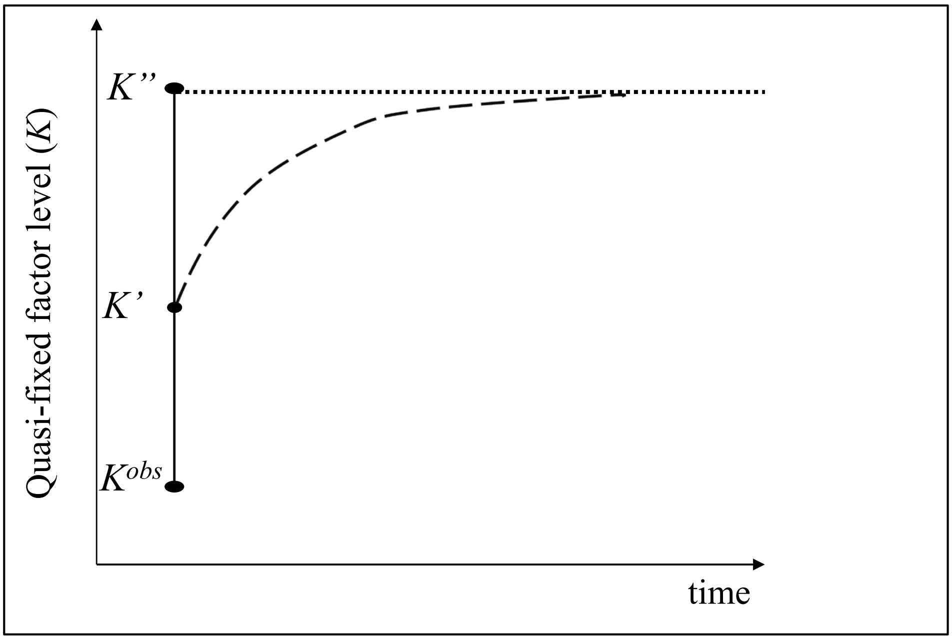
[12] The detailed procedure will be presented when the dynamic efficiency model under uncertainty is derived (cf. section 4).

adjustable in that period. These quasi-fixed factors follow an adjustment process to their long-run optimal value, which might be costly due to temporary production losses or transaction costs (Nemoto and Goto 1999, 2003; Rungsuriyawiboon 2003). Gardebroek and Oude Lansink (2008) state that if the existence of adjustment costs and the interdependence of production decisions over time are ignored, it may cause inaccurate measures of efficiency and firms may be seemingly inefficient.

The effect of considering adjustment costs is illustrated in Figure 13. K^{obs} represents an observation of the quasi-fixed input (*K*) of a firm at a particular time period.[13] The optimal adjustment of the quasi-fixed input over time is denoted by the curve starting at *K'*. *K''* represents the long-term optimal value of the quasi-fixed input. Static efficiency approaches assume that firms adjust the quasi-fixed input *K* immediately to the long-run optimal values *K''*. In contrast, dynamic efficiency approaches account for adjustment costs and the optimal adjustment path of quasi-fixed factors. Hence, an adjustment is only optimal up to the input level *K'* in the current time period and the factors will gradually be adjusted up to their long-term optimal value *K''* in the next periods. As a consequence, the basis for efficiency measurement differs since the approaches either refer to *K''* or *K'* as the cost-minimizing level of the quasi-fixed factor. This results in different levels of the efficiency scores (Gardebroek and Oude Lansink 2008).

13 The time index is left out in the figure for illustrating purposes.

Figure 13. Adjustment of quasi-fixed factors over time



Source: Adopted from Gardebroek and Oude Lansink (2008).

In addition to the dynamics of the production process, firms operate under uncertain environmental conditions and might be confronted with price uncertainty. This is particularly true for dairy farms in the EU since reduced price support and increasing quota levels have led to increasing milk and factor price volatility (e.g., Jongeneel et al. 2010; Keane and O'Connor 2009). Besides impacting the optimal demand of variable inputs, uncertainty may impact the optimal quasi-fixed factor demand (e.g., Pietola and Myers 2000; Pindyck 1991; Serra et al. 2010). Since efficiency measurement is based on optimal factor demand functions, considering uncertainty in the modeling approach for dynamic efficiency is crucial. This could affect the measurement of the efficiency scores being the basis for farm-level decision making or policy recommendations and has thus far not been considered in modeling dynamic efficiency.

4 Dynamic efficiency under uncertainty

In the following section,[14] a model accounting for price and output-level uncertainty in dynamic efficiency measurement is presented. The dynamic efficiency approach by Rungsuriyawiboon and Stefanou (2007) presented before has the advantage of a dynamic dual model and embeds both allocative and technical efficiency measures. Though these authors derive investment and variable input demand functions along with these efficiency parameters, their model assumes that the decision maker expects the current prices and technology to persist indefinitely in the future. Hence, the idea presented here is to merge models of investment under uncertainty and (deterministic) dynamic efficiency analysis (cf. Hüttel et al. 2011). First, the theoretical model is derived (4.1). This includes the cost minimization framework under uncertainty (4.1.1) and incorporating technical and allocative efficiency (4.1.2) to derive stochastic factor demand equations with embedded inefficiency parameters. Second, the value function which has to fulfil specific properties to ensure that the output and price uncertainty enter the factor demand functions is specified (4.2). Third, hypotheses on the influence of uncertainty on the optimal factor demand and the measurement of dynamic efficiency are derived (4.3).

4.1 Theoretical model derivation

4.1.1 Cost minimization under uncertainty

A representative firm is assumed to act in a way that it solves the infinite horizon problem such that the expected discounted sum of all future costs over an infinite planning horizon is minimized, subject to the production sequence and capital accumulation. The factor prices and the level of output are given in the base period (Epstein and Denny 1983). In contrast to Epstein and Denny (1983), future costs are assumed to be uncertain. By this, the approach of Rungsuriyawiboon and Stefanou (2007) is expanded on such that the model considers non-static input price and output-level expectations introducing an additional constraint.

The value function $J(\cdot)$ of this optimization problem is given by

[14] Parts of the following chapters are based on the paper "Dynamic efficiency of German dairy farms under uncertainty" which is under review. An earlier version is available as "Measuring Dynamic Efficiency under Uncertainty: An Application to German Dairy Farms", which was prepared for the Agricultural & Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting. The papers are the joint work of the author, as well as Silke Hüttel, Rashmi Narayana and Martin Odening.

$$J\left(w(0),c(0),y(0),K(0)\right)=\min_{x,I} E_0\int_0^{\infty} e^{-rt}\left[\sum_n\left(w_n(t)\cdot x_n(t)\right)+\sum_m\left(c_m(t)\cdot K_m(t)\right)\right]\cdot dt \tag{16}$$

subject to

$$y(t)\leq F\left(x(t),K(t),\dot{K}(t)\right) \tag{17}$$

$$\dot{K}_m(t)=\left(I_m(t)-\delta\cdot K_m(t)\right) \tag{18}$$

$$dz=\alpha\cdot dt+\psi\cdot dv \tag{19}$$

with $K(0)=K_0>0$, $K_m(t)>0$. Symbol t denotes time,[15] E_0 is the expectation operator conditional on information available at present time, $x_n(t)$ symbolizes the n^{th} variable factor, with $\left[x_1(t),\ldots,x_{\bar{n}}(t)\right]\in\Re_{+}^{\bar{n}}$ and $\left[w_1(t),\ldots,w_{\bar{n}}(t)\right]\in\Re_{++}^{\bar{n}}$ represent the factor prices with $n=1,...,\bar{n}$. Further, $K_m(t)$ denotes the m^{th} quasi-fixed input level with $\left[K_1(t),\ldots,K_{\bar{m}}(t)\right]\in\Re_{+}^{\bar{m}}$ and the quasi-fixed factor prices are given by $\left[c_1(t),\ldots,c_{\bar{m}}(t)\right]\in\Re_{++}^{\bar{m}}$. Moreover, $I_m(t)$ symbolizes gross investment in the m^{th} quasi-fixed factor with $m=1,...,\bar{m}$, and r is a constant discount rate. δ denotes a constant depreciation rate.

The first and second constraint (equations (17) and (18)) are equal to the constraints in Rungsuriyawiboon and Stefanou (2007) inheriting the same assumptions. The third constraint is different from their model and introduces uncertainty into the optimization problem. This constraint captures dynamics of a vector $z(t)$ containing logarithmized state variables: $\ln w_n(t)$, $\ln c_m(t)$ and $\ln y(t)$. The stochastic input price and output level development is modeled as an arithmetic Brownian motion as given in equation (19). Therein α denotes a vector of drift parameters and describes the expected increase of the state variables and ψ is a matrix satisfying $\psi\psi'=\Sigma$, where Σ is a variance covariance matrix given by $\Sigma=\begin{pmatrix}\sigma_{\ln y}^2 & \sigma_{\ln y,\ln w} & \sigma_{\ln y,\ln c}\\ \sigma_{\ln w,\ln y} & \sigma_{\ln w}^2 & \sigma_{\ln w,\ln c}\\ \sigma_{\ln c,\ln y} & \sigma_{\ln c,\ln w} & \sigma_{\ln c}^2\end{pmatrix}_{((1+\bar{n}+\bar{m})\times(1+\bar{n}+\bar{m}))}$. dv is a standard Wiener increment with

[15] The subscripts t (time dependency) and i (individuals) are suppressed wherever possible.

$E\{dv\}=0$, $E\{(dv)^2\}=dt$ and $E\{dv_t dv_{t'}\}=0$ for all $t \neq t'$ where t and t' denote two different time periods.

This constraint originates in the work of Pietola and Myers (2000). Commonly, dynamic dual models for analyzing investment decisions applied to agricultural problems assume that producers have static expectations about future prices (Gardebroek and Oude Lansink 2008; Emvalomatis 2009) and, thus, the intertemporal dimension of price uncertainty is not considered (Sckokai and Moro 2009). Pietola and Myers (2000) have developed an outstanding model with non-static expectations to investigate structural adjustment in the Finnish hog industry. This is achieved by generalizing the value function conditions derived by Luh and Stefanou (1996).[16] As a result, their model explicitly accounts for price and output uncertainty in the factor demand equations (cf. Pietola and Myers 2000). In the empirical application, these authors model uncertainty using a dummy variable for Finland's entry to the EU considering a shift from a stable period of protection to an uncertain environment associated with the EU entry. Their empirical results show that the estimated dummy variable coefficients are negative indicating that investments and labor negatively respond to increased uncertainty. In addition, these authors found that the adjustment to the long-run equilibrium is rather slow: the adjustment rate of labor amounts to 0.06 per year.

The stochastic optimization problem as given in equations (16)–(19) is solved using stochastic dynamic programming. The HJB equation is given by (Pietola and Myers 2000)

$$\begin{aligned} rJ(z,\, K) = \min_{x,I} \Bigg\{ & \sum_n \big(w_n \cdot x_n(t)\big) + \sum_m \big(c_m \cdot K_m(t)\big) + \sum_m \Big(J_{K_m} \cdot \big(I_m(t) - \delta \cdot K_m(t)\big)\Big) \\ & + \gamma(t) \cdot \Big[y(t) - F\big(x_n(t), K_m(t), \dot{K}_m(t)\big) \Big] + \sum_j J_{z_j} \cdot \alpha + \frac{1}{2} \cdot \Omega \Bigg\} \end{aligned} \tag{20}$$

where costs for variable and quasi-fixed factors are given by $\sum_n \big(w_n \cdot x_n(t)\big)$ and $\sum_m \big(c_m \cdot K_m(t)\big)$, respectively, and $\sum_m \Big(J_{K_m} \cdot \big(I_m(t) - \delta \cdot K_m(t)\big)\Big)$ denotes the imputed value of additional assets. In addition, $\gamma(t) \cdot \Big[y(t) - F\big(x_n(t), K_m(t), \dot{K}_m(t)\big) \Big]$ denotes the instantaneous change in the long-run cost (Rungsuriyawiboon 2003; Rungsuriyawiboon and Stefanou 2007) with $\gamma(t) = \partial J / \partial y$ as the co-state variable associated with the production target constraint

[16] Pietola and Myers (2000) show that, without generalizing, output and input price uncertainty would drop out from the optimal factor demand equations.

(Stefanou 1989). Equation (20) differs from the model proposed by Rungsuriyawiboon and Stefanou (2007) given in equation (15) by the last two terms: $\sum_j J_{z_j} \cdot \alpha + \frac{1}{2} \cdot \Omega$. Therein, J_{z_j} denotes partial derivatives of J with respect to vector z. Symbol Ω captures uncertainty of the state variable—output level and input prices—and is defined as $\Omega = \sum_{j=1}^{1+\bar{n}+\bar{m}} \sum_{j'=1}^{1+\bar{n}+\bar{m}} J_{z_j z_{j'}} \sigma_{jj'}$ where $J_{z_j z_{j'}}$ denotes the second-order partial derivatives of J with respect to the j and j'-th element of the vector of state variables and $\sigma_{jj'}$ is the jj'th element of the variance covariance matrix Σ.

The first derivatives of the HJB equation given in equation (20) with respect to (logarithmic) input prices—used since a stochastic price and output development is assumed as given in equation (19)—yield optimal decision rules under uncertainty (cf. Pietola and Myers 2000). The optimal net investment demand is given by

$$\dot{K}_m^* = \left(J_{K_m, \ln c_m}\right)^{-1} \left(rJ_{\ln c_m} - c_m \cdot K_m - \sum_{m' \neq m} \left(\dot{K}_{m'} \cdot J_{K_{m'}, \ln c_m} \right) - \alpha \cdot J_{z, \ln c_m} - \frac{1}{2} \cdot \Omega_{\ln c_m} \right) \tag{21}$$

and the optimal variable factor demand for the n^{th} variable input is given by

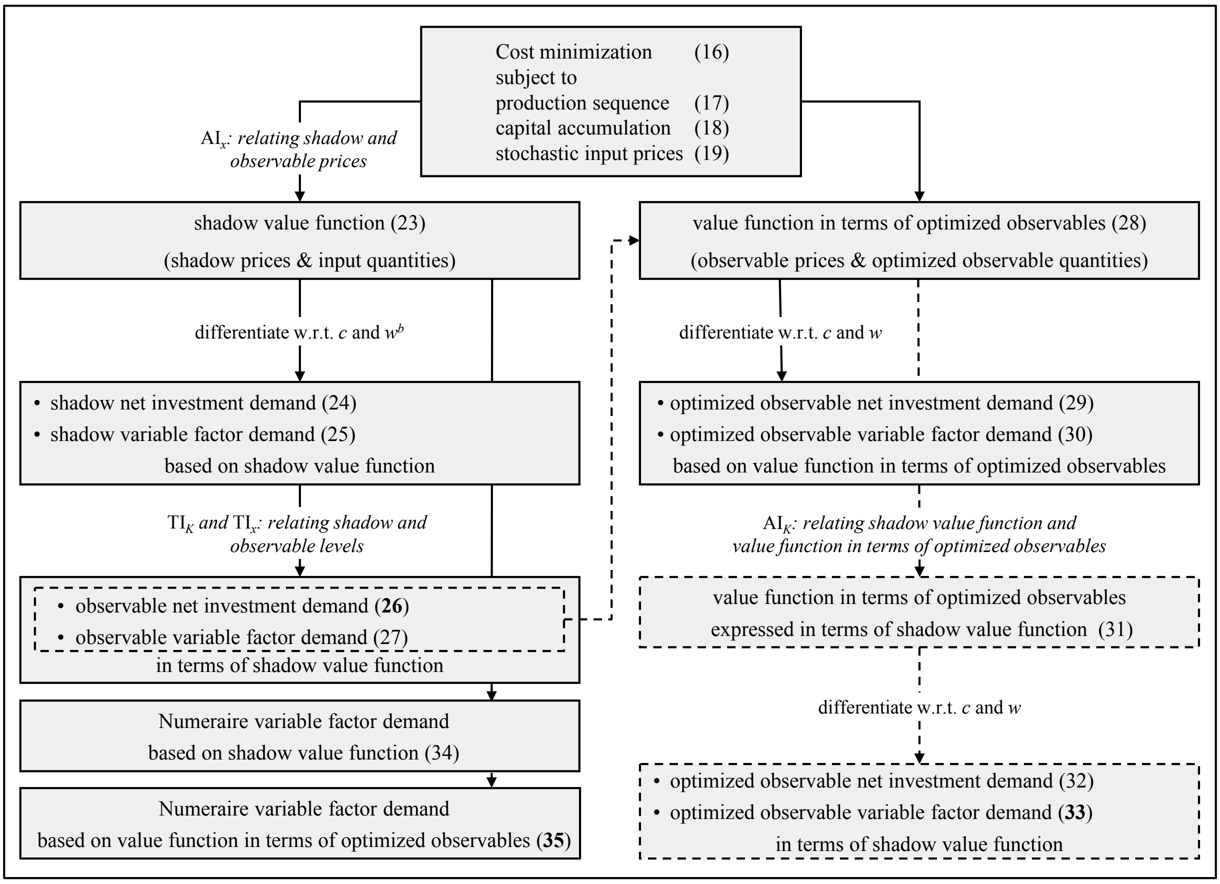
$$x_n^* = \frac{1}{w_n} \cdot \left(r \cdot J_{\ln w_n} - \sum_m \left(J_{K_m, \ln w_n} \cdot \dot{K}_m \right) - \alpha \cdot J_{z, \ln w_n} - \frac{1}{2} \cdot \Omega_{\ln w_n} \right). \tag{22}$$

Therein subscripts of J denote derivatives, and m' indicates the quasi-fixed factors other than m with $m' = 1, \ldots, \bar{m} \;\; \forall m' \neq m$. The optimal net investment demand for the m^{th} quasi-fixed factor depends on investments in other quasi-fixed factors indicated by $\sum_{m' \neq m} \left(\dot{K}_{m'} \cdot J_{K_{m'}, \ln c_m} \right)$. Symbols $\Omega_{\ln c_m}$ and $\Omega_{\ln w_n}$ account for production level and input price uncertainty and are derivatives of the $(1+\bar{n}+\bar{m}) \times (1+\bar{n}+\bar{m})$-matrix Ω with respect to $\ln c_m$ and $\ln w_n$, respectively. Equations (21) and (22) exemplify that uncertainty may affect the optimal quasi-fixed and variable factor decisions.

4.1.2 Technical and allocative efficiency

However, the factor demand equations (21) and (22) indicate that firms are assumed to be perfectly technical and allocative efficient. This might not be true: firms might either use too much input to produce a given amount of output or use a different than cost-minimizing combination of inputs given the respective prices. To measure possible inefficiency the shadow cost approach (cf. section 3.2) is used. For combining this approach and the dynamic dual model the procedure developed by Rungsuriyawiboon and Stefanou (2007) is applied. In contrast to Rungsuriyawiboon and Stefanou (2007) input prices and output level follow an arithmetic Brownian motion (cf. equation (19)). Hence, the differentiation of the respective Hamilton-Jacobi-Bellman equations is carried out with respect to the logarithms of prices to obtain the optimal factor demand equations (Shephard's Lemma). The procedure involves three major steps described in the following and Figure 14 provides an overview of the model derivation. The left-hand side of the figure corresponds to step one (shadow prices), the right part corresponds to the second step (observable prices) and the dotted lines denote the third step. The numbers inside the parentheses correspond to the equations in the theoretical model and the bold numbers indicate the final equations that serve as a base for the empirical model.

Figure 14. Procedure of dynamic efficiency measurement under uncertainty



Note: AI: allocative inefficiency, TI: technical inefficiency, c: observable quasi-fixed factor prices, w: observable variable factor prices, w^b: shadow prices of variable factors, x: variable factor level, K: quasi-fixed factor level.

First step The shadow[17] value function J^b is defined using the shadow prices given by $w_n^b = \lambda_n w_n$. Minimizing the shadow value function leads to the shadow HJB equation that can be written as

$$\begin{aligned} rJ^b\left(w_n^b(t), c_m(t), K_m(t), y(t)\right) = & \sum_n \left(w_n^b(t) \cdot x_n^b(t)\right) + \sum_m \left(c_m(t) \cdot K_m(t)\right) \\ & + \sum_m \left(J_{K_m}^b \cdot \left(I_m(t) - \delta \cdot K_m(t)\right)\right) \\ & + \gamma^b(t) \cdot \left[y(t) - F\left(x_n^b(t), K_m(t), \dot{K}_m^b(t)\right)\right] \\ & + \sum_j J_{z_j}^b \cdot \alpha + \frac{1}{2} \cdot \Omega^b \end{aligned} \tag{23}$$

wherein $w_n^b = \lambda_n w_n$ indicate that the unobservable shadow prices w_n^b may deviate from observable prices w_n by λ_n. Symbol λ_n measures allocative inefficiency such that values $\lambda_n > 1$ (< 1) indicate that less (more) of the n^{th} input is used compared to the cost-minimizing (efficient) allocation with respect to the observable prices. The shadow variable factor demand is symbolized by x_n^b and is assumed to be the technically efficient level of variable inputs. $J_{K_m}^b$ denotes marginal value of the shadow capital stock which may deviate from the marginal value of the actual capital stock $J_{K_m}^a$ through the allocative inefficiency parameter of net investments: $J_{K_m}^b = \mu_m \cdot J_{K_m}^a$. Thereby values of $\mu_m > 1$ (< 1) imply that the m^{th} quasi-fixed factor is underused (overused). Symbol $\gamma^b(t) \geq 0$ is the shadow short-run marginal cost of production (Rungsuriyawiboon and Stefanou 2007) and $J_{z_j}^b$ denotes derivatives of J^b with respect to vector z. Furthermore, $\Omega^b = \sum_{j=1}^{1+\bar{n}+\bar{m}} \sum_{j'=1}^{1+\bar{n}+\bar{m}} J_{z_j z_{j'}}^b \sigma_{jj'}$ where $J_{z_j z_{j'}}^b$ denotes the respective second partial derivatives of J^b with respect to vector z.

The first derivatives of equation (23) with respect to the input prices $\ln c_m$ and $\ln w_n$ yield the shadow factor demand equations under uncertainty. In order to reduce the complexity of the model a zero drift rate of the Brownian Motion in equation (19) is assumed such that $\alpha = 0$. The shadow net investment demand function for the m^{th} quasi-fixed input is given by

---

[17] Superscript ^{b} refers to shadow values and observed values are indicated by superscript ^{a}.

$$\dot{K}_m^b = \left(J_{K_m,\ln c_m}^b\right)^{-1}\left(rJ_{\ln c_m}^b - c_m \cdot K_m - \sum_{m'\neq m}\left(\dot{K}_{m'}^b \cdot J_{K_{m'},\ln c_m}^b\right) - \frac{1}{2}\cdot\Omega_{\ln c_m}^b\right) \tag{24}$$

and the shadow variable factor demand for the n^{th} variable input is given by

$$x_n^b = \frac{1}{w_n^b}\cdot\left(rJ_{\ln w_n}^b - \sum_m\left(J_{K_m,\,\ln w_n}^b \cdot \dot{K}_m^b\right) - \frac{1}{2}\cdot\Omega_{\ln w_n}^b\right) \tag{25}$$

where uncertainty is captured by the term $\Omega_{\ln c_m}^b$ and $\Omega_{\ln w_n}^b$ denoting the derivative of the $(1+\overline{n}+\overline{m})\times(1+\overline{n}+\overline{m})$-matrix Ω^b with respect to $\ln c_m$ and $\ln w_n$, respectively.

The cost-minimizing factor demand levels under the shadow prices, x_n^b and $\dot{K}_m^b$, may differ from the demanded quantities under observable conditions by technical inefficiency. Technical inefficiency for net investment is denoted by $\tau_K \geq 1$ and for the variable input by $\tau_x \geq 1$ such that $\dot{K}_m^b = \left(1/\tau_K\right)\cdot\dot{K}_m$ and $x_n^b = \left(1/\tau_x\right)\cdot x_n$. In contrast to the allocative efficiency, technical efficiency measurement is not input specific. Based upon this definition, observable factor demand functions are expressed as functions of the technical inefficiency measures

$$\dot{K}_m = \tau_K \cdot \dot{K}_m^b = \tau_K \cdot \left(J_{K_m,\ln c_m}^b\right)^{-1}\left(rJ_{\ln c_m}^b - c_m \cdot K_m - \sum_{m'\neq m}\left(\dot{K}_{m'}^b \cdot J_{K_{m'},\ln c_m}^b\right) - \frac{1}{2}\cdot\Omega_{\ln c_m}^b\right) \tag{26}$$

$$x_n = \tau_x \cdot x_n^b = \frac{\tau_x}{w_n^b}\cdot\left(rJ_{\ln w_n}^b - \sum_m\left(J_{K_m,\,\ln w_n}^b \cdot \dot{K}_m^b\right) - \frac{1}{2}\cdot\Omega_{\ln w_n}^b\right). \tag{27}$$

Second step Next, the perfect efficient condition is introduced: the observable input quantities (x_n and $\dot{K}_m$) are assumed to be the optimal ones, that is, the cost-minimizing factor demand levels with respect to the observable prices (cf. Rungsuriyawiboon and Hockmann 2012). The corresponding value function in terms of observables is optimized with respect to the observed prices. The resulting optimized observable quantities—denoted by x_n^o and $\dot{K}_m^o$— represent thus a fully efficient input use and according to that, the variable and quasi-fixed factor demand equations contain no inefficiency terms. The optimized observable HJB corresponding to the value function in terms of optimized observables is given by

$$rJ^a = \sum_n\left(w_n \cdot x_n^o\right) + \sum_m\left(c_m \cdot K_m\right) + \sum_m\left(J_{K_m}^a \cdot \dot{K}_m^o\right) + \frac{1}{2}\cdot\Omega^a \tag{28}$$

where $\Omega^a = \sum_{j=1}^{1+\bar{n}+\bar{m}} \sum_{j'=1}^{1+\bar{n}+\bar{m}} J^a_{z_j z_{j'}} \sigma_{jj'}$.[18]

Differentiating equation (28) with respect to $\ln c_m$ and $\ln w_n$ yields the optimized observable net investment and variable factor demand equations under perfect efficiency

$$\dot{K}^o_m = \left(J^a_{K_m,\ln c_m}\right)^{-1}\left(rJ^a_{\ln c_m} - c_m \cdot K_m - \sum_{m'\neq m}\left(\dot{K}^o_{m'} \cdot J^a_{K_{m'},\ln c_m}\right) - \frac{1}{2}\cdot\Omega^a_{\ln c_m}\right) \tag{29}$$

$$x^o_n = \frac{1}{w_n}\cdot\left(r\cdot J^a_{\ln w_n} - \sum_m\left(J^a_{K_m,\ln w_n}\cdot\dot{K}^o_m\right) - \frac{1}{2}\cdot\Omega^a_{\ln w_n}\right). \tag{30}$$

Third step The inefficiency measures are integrated into the optimized observable factor demand. Cost inefficiency is defined as the deviation between the value function in terms of optimized observables and the shadow value function. To accommodate the deviancy, the value function in terms of optimized observables is expressed in terms of the shadow value function. To this end, the optimized observable terms as derived in the second step are substituted by their shadow counterparts: in the optimized observable HJB equation given in equation (28), $J^a_{K_m}$ is substituted by $\left(1/\mu_m\right)\cdot J^b_{K_m}$, x^o_n by equation (27), $\dot{K}^o_m$ by equation (26) and Ω^a is substituted by Ω^b. The optimized observable HJB equation is expressed in terms of the shadow value function as follows

$$\begin{aligned} rJ^a = &\sum_n\left\{\frac{\tau_x}{\lambda_n}\left[rJ^b_{\ln w_n} - \sum_m\left\{\frac{J^b_{K_m,\ \ln w_n}}{J^b_{K_m,\ln c_m}}\left(rJ^b_{\ln c_m} - c_m K_m - \sum_{m'\neq m}\left(\dot{K}^b_{m'}J^b_{K_{m'},\ln c_m}\right) - \frac{\Omega^b_{\ln c_m}}{2}\right)\right\} - \frac{\Omega^b_{\ln w_n}}{2}\right]\right\} \\ &+\sum_m\left\{\frac{\tau_K}{\mu_m}\frac{J^b_{K_m}}{J^b_{K_m,\ln c_m}}\left(r\cdot J^b_{\ln c_m} - c_m K_m - \sum_{m'\neq m}\left(\dot{K}^b_{m'}J^b_{K_{m'},\ln c_m}\right) - \frac{\Omega^b_{\ln c_m}}{2}\right)\right\} + \frac{\Omega^b}{2} + \sum_m\left(c_m K_m\right). \end{aligned} \tag{31}$$

Differentiating equation (31) with respect to $\ln c_m$, with respect to first K_m and then $\ln c_m$ and finally first with respect to $K_{m'}$ and then $\ln c_m$, and substituting the derivatives into equation (29) yields the m^{th} optimized observable net investment demand in terms of the shadow value function.[19]

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[18] Therein $J^a_{z_j z_{j'}}$ denotes the respective second partial derivatives of J^a with respect to vector z .

[19] Note that any derivatives higher than the second order of J^b are ignored. The respective factor in use is indicated in bold letters to improve the readability.

$$
\begin{aligned}
&\Bigg\{\frac{1}{r}\sum_n \frac{\tau_x}{\lambda_n}\Bigg(\frac{J^b_{K_{\mathbf{m}},\ln w_n}}{J^b_{K_{\mathbf{m}},\ln c_{\mathbf{m}}}}\cdot c_{\mathbf{m}}\Bigg)+\frac{1}{r}\Bigg(1-\frac{\tau_K}{\mu_{\mathbf{m}}}\Bigg)c_{\mathbf{m}}-\frac{\tau_K}{r\mu_{\mathbf{m}}}\Bigg(\frac{J^b_{K_{\mathbf{m}}}}{J^b_{K_{\mathbf{m}},\ln c_{\mathbf{m}}}}\cdot c_{\mathbf{m}}\Bigg)\\
&\quad+\sum_m \frac{\tau_K}{\mu_m}\Bigg(\frac{J^b_{\ln c_m,K_{\mathbf{m}}}\cdot J^b_{K_m,\ln c_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}+\frac{J^b_{K_m,K_{\mathbf{m}}}\cdot J^b_{\ln c_m,\ln c_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}\Bigg)\\
&\quad-\frac{\tau_K}{r\mu_{\mathbf{m}}}\Bigg(\frac{J^b_{K_{\mathbf{m}},K_{\mathbf{m}}}}{J^b_{K_{\mathbf{m}},\ln c_{\mathbf{m}}}}\cdot c_{\mathbf{m}}K_{\mathbf{m}}\Bigg)+\frac{\Omega^b_{K_{\mathbf{m}},\ln c_{\mathbf{m}}}}{2r}\\
&\quad-\frac{1}{2r}\sum_m\Bigg[\frac{\tau_K}{\mu_m}\Bigg(\Omega^b_{\ln c_m,K_{\mathbf{m}}}\cdot\frac{J^b_{K_m,\ln c_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}+\frac{J^b_{K_m,K_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}\cdot\Omega^b_{\ln c_m,\ln c_{\mathbf{m}}}\Bigg)\Bigg]\Bigg\}\dot{K}^o_{\mathbf{m}}=\\
&\sum_n\frac{\tau_x}{\lambda_n}\cdot rJ^b_{\ln w_n,\ln c_{\mathbf{m}}}-\sum_n\frac{r\tau_x}{\lambda_n}\sum_m\Bigg(\frac{J^b_{K_m,\ln w_n}\cdot J^b_{\ln c_m,\ln c_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}\Bigg)-\sum_n\frac{\tau_x}{2\lambda_n}\cdot\Omega^b_{\ln w_n,\ln c_{\mathbf{m}}}\\
&+\sum_n\frac{\tau_x}{\lambda_n}\Bigg(\frac{J^b_{K_{\mathbf{m}},\ln w_n}}{J^b_{K_{\mathbf{m}},\ln c_{\mathbf{m}}}}\cdot c_{\mathbf{m}}K_{\mathbf{m}}\Bigg)+\sum_n\frac{\tau_x}{2\lambda_n}\cdot\sum_m\Bigg(\frac{J^b_{K_m,\ln w_n}}{J^b_{K_m,\ln c_m}}\cdot\Omega^b_{\ln c_m,\ln c_{\mathbf{m}}}\Bigg)\\
&+\sum_m\frac{r\tau_K}{\mu_m}\cdot\Bigg(\frac{J^b_{K_m}\cdot J^b_{\ln c_m,\ln c_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}+\frac{J^b_{\ln c_m}\cdot J^b_{K_m,\ln c_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}\Bigg)-\frac{\tau_K}{\mu_{\mathbf{m}}}\cdot\Bigg(\frac{J^b_{K_{\mathbf{m}}}}{J^b_{K_{\mathbf{m}},\ln c_{\mathbf{m}}}}\cdot c_{\mathbf{m}}K_{\mathbf{m}}\Bigg)\\
&-\sum_m\frac{\tau_K}{\mu_m}\Bigg(c_mK_m\cdot\frac{J^b_{K_m,\ln c_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}\Bigg)-\sum_m\frac{\tau_K}{\mu_m}\Bigg(\Bigg(\sum_{m'\neq\mathbf{m}}\Big(\dot{K}^b_{m'}\cdot J^b_{K_{m'},\ln c_{\mathbf{m}}}\Big)\Bigg)\cdot\frac{J^b_{K_m,\ln c_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}\Bigg)\\
&-\sum_m\frac{\tau_K}{2\mu_m}\Bigg(\frac{J^b_{K_m}}{J^b_{K_m,\ln c_m}}\cdot\Omega^b_{\ln c_m,\ln c_{\mathbf{m}}}+\Omega^b_{\ln c_m}\cdot\frac{J^b_{K_m,\ln c_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}\Bigg)\\
&-\sum_{\substack{m'=1\\ \forall m'\neq m}}^{\bar{m}}\Bigg\{\dot{K}^o_{m'}\Bigg[\sum_m\frac{\tau_K}{\mu_m}\Bigg(\frac{J^b_{\ln c_m,K_{m'}}\cdot J^b_{K_m,\ln c_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}+\frac{J^b_{K_m,K_{m'}}\cdot J^b_{\ln c_m,\ln c_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}\Bigg)+\frac{\Omega^b_{K_{m'},\ln c_{\mathbf{m}}}}{2r}\\
&-\frac{\tau_K}{r\mu_{m'}}\Bigg(c_{m'}\cdot\frac{J^b_{K_{m'},\ln c_{\mathbf{m}}}}{J^b_{K_{m'},\ln c_{m'}}}\Bigg)-\frac{\tau_K}{r\mu_{\mathbf{m}}}\Bigg(\frac{J^b_{K_{\mathbf{m}},K_{m'}}}{J^b_{K_{\mathbf{m}},\ln c_{\mathbf{m}}}}\cdot c_{\mathbf{m}}K_{\mathbf{m}}\Bigg)\\
&-\frac{1}{2r}\sum_m\frac{\tau_K}{\mu_m}\Bigg(\Omega^b_{\ln c_m,K_{m'}}\cdot\frac{J^b_{K_m,\ln c_{\mathbf{m}}}}{J^b_{K_m,\ln c_m}}+\frac{J^b_{K_m,K_{m'}}}{J^b_{K_m,\ln c_m}}\cdot\Omega^b_{\ln c_m,\ln c_{\mathbf{m}}}\Bigg)\Bigg]\Bigg\}
\end{aligned}
\qquad (32)
$$

Similarly, inserting the derivatives of equation (31) with respect to $\ln w_n$ as well as with respect to K_m and $\ln w_n$ into equation (30) yields the optimized observable factor demand expressed in terms of the shadow value function—serving as a base for the empirical model—for the n^{th} variable input.[20]

[20] Note that any derivatives higher than the second order of J^b are ignored. The respective factor in use is indicated in bold letters to improve the readability.

$$
\begin{aligned}
x_{\boldsymbol{n}}^{o} = \frac{1}{w_{\boldsymbol{n}}} \Bigg\{ & r\tau_x \sum_n \frac{1}{\lambda_n} \cdot J^b_{\ln w_n, \ln w_{\boldsymbol{n}}} - r\tau_x \sum_n \left[\frac{1}{\lambda_n} \sum_m \frac{J^b_{K_m, \ln w_n} \cdot J^b_{\ln c_m, \ln w_{\boldsymbol{n}}}}{J^b_{K_m, \ln c_m}} \right] \\
& + \frac{\tau_x}{2} \sum_n \left[\frac{1}{\lambda_n} \sum_m \frac{J^b_{K_m, \ln w_n} \cdot \Omega^b_{\ln c_m, \ln w_{\boldsymbol{n}}}}{J^b_{K_m, \ln c_m}} \right] - \frac{\tau_K}{2} \sum_m \left[\frac{1}{\mu_m} \cdot \left(\frac{J^b_{K_m} \cdot \Omega^b_{\ln c_m, \ln w_{\boldsymbol{n}}} + J^b_{K_m, \ln w_{\boldsymbol{n}}} \cdot \Omega^b_{\ln c_m}}{J^b_{K_m, \ln c_m}} \right) \right] \\
& + r\tau_K \sum_m \left[\frac{1}{\mu_m} \cdot \left(\frac{J^b_{K_m} \cdot J^b_{\ln c_m, \ln w_{\boldsymbol{n}}} + J^b_{\ln c_m} \cdot J^b_{K_m, \ln w_{\boldsymbol{n}}}}{J^b_{K_m, \ln c_m}} \right) \right] - \tau_K \sum_m \left[\frac{1}{\mu_m} \cdot \frac{c_m \cdot K_m \cdot J^b_{K_m, \ln w_{\boldsymbol{n}}}}{J^b_{K_m, \ln c_m}} \right] \\
& - \tau_K \sum_m \left[\frac{1}{\mu_m} \cdot \frac{J^b_{K_m, \ln w_{\boldsymbol{n}}}}{J^b_{K_m, \ln c_m}} \cdot \sum_{m' \neq m} \left(\dot{K}^b_{m'} \cdot J^b_{K_{m'}, \ln c_m} \right) \right] - \tau_K \sum_{\boldsymbol{m}} \left[\dot{K}^o_{\boldsymbol{m}} \sum_m \left[\frac{1}{\mu_m} \cdot \frac{J^b_{K_m, K_{\boldsymbol{m}}} \cdot J^b_{\ln c_m, \ln w_{\boldsymbol{n}}}}{J^b_{K_m, \ln c_m}} \right] \right] \qquad (33) \\
& - \tau_K \sum_{\boldsymbol{m}} \left[\dot{K}^o_{\boldsymbol{m}} \sum_m \left[\frac{1}{\mu_m} \cdot \frac{J^b_{\ln c_m, K_{\boldsymbol{m}}} \cdot J^b_{K_m, \ln w_{\boldsymbol{n}}}}{J^b_{K_m, \ln c_m}} \right] \right] - \frac{\tau_x}{2} \sum_n \frac{1}{\lambda_n} \cdot \Omega^b_{\ln w_n, \ln w_{\boldsymbol{n}}} \\
& - \frac{1}{2r} \sum_m \left[\dot{K}^o_m \cdot \Omega^b_{K_m, \ln w_{\boldsymbol{n}}} \right] + \frac{\tau_K}{2r} \sum_{\boldsymbol{m}} \left[\dot{K}^o_{\boldsymbol{m}} \sum_m \left[\frac{1}{\mu_m} \cdot \frac{\Omega^b_{\ln c_m, K_{\boldsymbol{m}}} \cdot J^b_{K_m, \ln w_{\boldsymbol{n}}}}{J^b_{K_m, \ln c_m}} \right] \right] \\
& + \frac{\tau_K}{r} \sum_m \left[\dot{K}^o_m \left(\frac{1}{\mu_m} \cdot \frac{c_m \cdot J^b_{K_m, \ln w_{\boldsymbol{n}}}}{J^b_{K_m, \ln c_m}} \right) \right] + \frac{\tau_K}{2r} \sum_{\boldsymbol{m}} \left[\dot{K}^o_{\boldsymbol{m}} \sum_m \left[\frac{1}{\mu_m} \cdot \frac{J^b_{K_m, K_{\boldsymbol{m}}} \cdot \Omega^b_{\ln c_m, \ln w_{\boldsymbol{n}}}}{J^b_{K_m, \ln c_m}} \right] \right] \Bigg\}
\end{aligned}
$$

Variable factor demand as presented in equation (33) is inversely related to its price and further a function of net investment, the respective level of the quasi-fixed factors and their prices. The structure of equation (33) differs from the deterministic factor demand equation through the risk dependent term Ω. The price uncertainties (enclosed in $\Omega^b_{\ln w_n, \ln w_{\boldsymbol{n}}}$ and $\Omega^b_{K_m, \ln w_{\boldsymbol{n}}}$) negatively influence the variable input demand, but the impact of the cross derivatives is difficult to assess a priori due to complex interactions. Moreover, all measures for technical and allocative inefficiencies enter the equation on the right-hand side as well and determine the observable demanded factor-level. Notably, the inner arguments—consisting of the value function derivatives and the Ω's—are scaled interactively by the inefficiency terms: either by τ_K combined with μ_m or by τ_x together with λ_n.

The variable factor prices are normalized by using the first variable factor price as a numeraire in order to satisfy the property of linear homogeneity in prices of the cost function (cf. Maietta 2000). The shadow prices are redefined as $w_n^b = \left(\lambda_n w_n / \lambda_1 w_1 \right) = \lambda_{n1} w_{n1}$. Symbol λ_{n1} accounts for price distortions of the n^{th} variable factor relative to the numeraire variable factor. Values of $\lambda_{n1} > 1$ (< 1) imply that the ratio of the shadow price of the n^{th} variable factor relative to the numeraire is higher (lower) than the respective observed prices ratio. This indicates an underuse (overuse) of the n^{th} variable factor in relation to the numeraire factor. In order to obtain the factor demand for the numeraire input, equation (23) is re-arranged; that is, the numeraire variable is singled out. The shadow demand x_1^b which may differ from the observed demand by technical inefficiency is given by

$$x_1^b = rJ^b - \sum_{n=2}^{\bar{n}} \left(w_n^b \cdot x_n^b \right) - \sum_m \left(c_m \cdot K_m \right) - \sum_m \left(J_{K_m}^b \cdot \dot{K}_m^b \right) - \frac{1}{2} \cdot \Omega^b . \tag{34}$$

Accordingly, under possible inefficiency, the optimized observable demand for the numeraire in the presence of uncertainty is given by

$$x_1^o = \tau_x \cdot \left(x_1^b \right) = \tau_x \cdot \left(rJ^b - \sum_{n=2}^{\bar{n}} \left(w_n^b \cdot x_n^b \right) - \sum_m \left(c_m \cdot K_m \right) - \sum_m \left(J_{K_m}^b \cdot \dot{K}_m^b \right) - \frac{1}{2} \cdot \Omega^b \right). \tag{35}$$

The estimation is based on the optimized observable variable input demand in terms of the shadow value function as presented in equations (33) and (35). In line with Rungsuriyawiboon and Stefanou (2007), equation (26) is used, however, to estimate investment demand because of the complex structure of its optimized observable counterpart in terms of the shadow value function (cf. equation (32)).

4.2 Value function specification

The estimation of the factor demand equations (26), (33) and (35) requires a specification of the value function in equation (16). This is challenging because in the case of a stochastic state vector z standard assumption of the cost function would impose 4th order derivative restrictions on the value function. Fortunately, Pietola and Myers (2000) have derived simpler conditions for the value function to ensure the desired properties of the cost function. These authors prove that the requirement that the cost function is convex in I and concave in w and c is fulfilled if J is concave in w and c, J_K is linear in w and c, J_z is quadratic and J_{zz} is linear in w and c, respectively.[21] A specification that fulfils the aforementioned properties is given by (cf. Epstein 1981; Hüttel et al. 2011)[22]

[21] Pietola and Myers (2000) impose further assumptions on the drift process α which are trivially fulfilled under the assumption $\alpha = 0$.

[22] For notational convenience and readability the matrix notation is used here.

$$J^b(\mathbf{z},\mathbf{K}) = a_0 + \begin{pmatrix} b'_K & b'_y & b'_w & b'_c \end{pmatrix} \begin{pmatrix} \mathbf{K} \\ \ln \mathbf{y} \\ \ln \mathbf{w^b} \\ \ln \mathbf{c} \end{pmatrix}$$

$$+\frac{1}{2}\begin{pmatrix} \mathbf{K}' & (\ln \mathbf{y})' & (\ln \mathbf{w^b})' & (\ln \mathbf{c})' \end{pmatrix} \begin{bmatrix} A_{KK} & A'_{yK} & 0 & 0 \\ A_{yK} & A_{yy} & A'_{wy} & A'_{cy} \\ 0 & A_{wy} & A_{ww} & A'_{cw} \\ 0 & A_{cy} & A_{cw} & A_{cc} \end{bmatrix} \begin{pmatrix} \mathbf{K} \\ \ln \mathbf{y} \\ \ln \mathbf{w^b} \\ \ln \mathbf{c} \end{pmatrix} \tag{36}$$

$$+\mathbf{c}'\mathbf{M}^{-1}\mathbf{K} + \mathbf{w^{b}}'\mathbf{A}_{wK}\mathbf{K}$$

wherein $\mathbf{K}$ refers to a vector of quasi-fixed inputs, $\ln \mathbf{y}$ denotes the scalar of logarithmic output and a_0 is an unknown constant parameter. $\ln \mathbf{w^b}$ and $\ln \mathbf{c}$ denote vectors containing the logarithms of the normalized variable input prices—the 1st variable input price is taken as a numeraire—and of the quasi-fixed factor prices, respectively. First-order value function parameters are represented by $\mathbf{b}' = \begin{pmatrix} b'_K & b'_y & b'_w & b'_c \end{pmatrix}$ and $\mathbf{A} = \begin{bmatrix} A_{KK} & A'_{yK} & 0 & 0 \\ A_{yK} & A_{yy} & A'_{wy} & A'_{cy} \\ 0 & A_{wy} & A_{ww} & A'_{cw} \\ 0 & A_{cy} & A_{cw} & A_{cc} \end{bmatrix}$ contains second-order value function parameters (cf. Hüttel et al. 2011). Due to the zero restrictions in $\mathbf{A}$ it is guaranteed that J_K and J_{zz} are linear in the quasi-fixed input prices. In contrast to non-stochastic models, the last term $\mathbf{c}'\mathbf{M}^{-1}\mathbf{K} + \mathbf{w^{b}}'\mathbf{A}_{wK}\mathbf{K}$ enters the shadow value function to ensure that J^b_z is quadratic *w* and *c* and J^b_{zz} is linear in *w* and *c*. Thereby $\mathbf{M}$ and $\mathbf{A}_{Kw}$ indicate matrices where $\mathbf{M}$ consists of adjustment parameters (cf. Hüttel et al. 2011).

Using the shadow value function specification as presented in equation (36) and its respective derivatives, the *m*th optimized observable net investment demand $\dot{K}^o_{\boldsymbol{m}}$ (cf. equation (26)) is specified in terms of the value function parameters and given by

$$\dot{K}^o_{\boldsymbol{m}} = \tau_K \cdot \left(M_{c_{\boldsymbol{m}}K_m} \cdot c^{-1}_{\boldsymbol{m}}\right) \cdot \left\{ r\left[b_{c_{\boldsymbol{m}}} + A_{c_{\boldsymbol{m}}y} \cdot \ln y + \sum_{n=2}^{\bar{n}} A_{c_{\boldsymbol{m}}w_n} \cdot \ln w^b_n + \sum_{m=1}^{\bar{m}} A_{c_{\boldsymbol{m}}c_m} \cdot \ln c_m \right.\right.$$
$$\left. + c_{\boldsymbol{m}} \cdot \left(\sum_{m=1}^{\bar{m}} M^{-1}_{c_{\boldsymbol{m}}K_m} \cdot K_m \right) \right] - c_{\boldsymbol{m}} \cdot K_{\boldsymbol{m}} - \sum_{m'=1, m' \neq \boldsymbol{m}}^{\bar{m}} \dot{K}^b_{m'} \cdot \left(M^{-1}_{c_{\boldsymbol{m}}K_{m'}} \cdot c_{\boldsymbol{m}} \right) \tag{37}$$
$$\left. - \frac{1}{2} \cdot \left(\sum_{m=1}^{\bar{m}} M^{-1}_{c_{\boldsymbol{m}}K_m} \cdot K_m \right) \cdot c_{\boldsymbol{m}} \cdot \sigma^2_{\ln c_{\boldsymbol{m}}} \right\}$$

where $M_{c_m K_m}$ represents the diagonal elements of the matrix $\mathbf{M}$. The b-parameters represent first-order parameters and the A-parameters represent second-order parameters of the value function. The last term $\left(\sum_{m=1}^{\bar{m}} M_{c_m K_m}^{-1} \cdot K_m\right) \cdot c_m \cdot \sigma_{\ln c_m}^2$ arises from the differentiation of Ω^b with respect to the m^{th} quasi-fixed factor price (cf. equation (26)). The term $\sigma_{\ln c_m}^2$ denotes the variance of the m^{th} (logarithmic) quasi-fixed factor price.

The n^{th} optimized observable variable input demand function (33) in terms of the value function (36) is given by

$$
\begin{aligned}
x_n^o = \frac{1}{w_n} \cdot \Bigg\{ & r \cdot \frac{\tau_x}{\lambda_n} \cdot \left(A_{w_n w_n} + \sum_{m=1}^{\bar{m}} \left(A_{w_n K_m} \cdot K_m \right) \cdot w_n^b \right) \\
& - \sum_{n=2}^{\bar{n}} \left[\frac{\tau_x}{\lambda_n} \cdot r \sum_{m=1}^{\bar{m}} \left(\frac{M_{c_m K_m}}{c_m} \cdot \left(A_{w_n K_m} \cdot w_n^b \right) \cdot A_{c_m w_n} \right) \right] \\
& - \frac{1}{2} \cdot \frac{\tau_x}{\lambda_n} \cdot \left(\sum_{m=1}^{\bar{m}} A_{w_n K_m} \cdot K_m \right) \cdot w_n^b \cdot \sigma_{\ln w_n}^2 + r \cdot \sum_{m=1}^{\bar{m}} \Bigg[\frac{\tau_K}{\mu_m} \cdot \left(\frac{M_{c_m K_m}}{c_m} \right) \cdot A_{c_m w_n} \cdot \\
& \left(b_{K_m} + \sum_{m=1}^{\bar{m}} \left(A_{K_m K_m} \cdot K_m \right) + A_{y K_m} \cdot \ln y + \sum_{m=1}^{\bar{m}} \left(M_{c_m K_m}^{-1} \cdot c_m \right) + \sum_{n=2}^{\bar{n}} \left(A_{w_n K_m} \cdot w_n^b \right) \right) \Bigg] \\
& + r \cdot \sum_{m=1}^{\bar{m}} \Bigg[\frac{\tau_K}{\mu_m} \cdot \Bigg(b_{c_m} + A_{c_m y} \cdot \ln y + \sum_{n=2}^{\bar{n}} \left(A_{c_m w_n} \cdot \ln w_n^b \right) + \sum_{m=1}^{\bar{m}} \left(A_{c_m c_m} \cdot \ln c_m \right) \\
& + c_m \cdot \sum_{m=1}^{\bar{m}} \left(M_{c_m K_m}^{-1} \cdot K_m \right) \Bigg) \cdot \left(\frac{M_{c_m K_m}}{c_m} \right) \cdot \left(A_{w_n K_m} \cdot w_n^b \right) \Bigg] \\
& - \sum_{m=1}^{\bar{m}} \left[\frac{\tau_K}{\mu_m} \cdot \left(K_m \cdot M_{c_m K_m} \cdot \left(A_{w_n K_m} \cdot w_n^b \right) \right) \right] \\
& - \sum_{m=1}^{\bar{m}} \left[\frac{\tau_K}{\mu_m} \cdot \left(\sum_{m'=1, m' \neq m}^{\bar{m}} \dot{K}_{m'}^b \cdot M_{c_{m'} K_m}^{-1} \right) \cdot M_{c_m K_m} \cdot \left(A_{w_n K_m} \cdot w_n^b \right) \right] \\
& - \frac{1}{2} \cdot \sum_{m=1}^{\bar{m}} \left[\frac{\tau_K}{\mu_m} \cdot \left(\sum_{m=1}^{\bar{m}} M_{c_m K_m}^{-1} \cdot K_m \right) \sigma_{\ln c_m}^2 \cdot M_{c_m K_m} \cdot \left(A_{w_n K_m} \cdot w_n^b \right) \right] \\
& - \sum_{m=1}^{\bar{m}} \left[\sum_{m=1}^{\bar{m}} \left[\frac{\tau_K}{\mu_m} \cdot \left(\left(c_m \cdot M_{c_m K_m}^{-1} \right) \cdot \left(A_{w_n K_m} \cdot w_n^b \right) + A_{K_m K_m} \cdot A_{c_m w_n} \right) \cdot \frac{M_{c_m K_m}}{c_m} \right] \cdot \dot{K}_m^o \right] \\
& + \frac{1}{r} \cdot \sum_{m=1}^{\bar{m}} \left[\frac{\tau_K}{\mu_m} \cdot \left(M_{c_m K_m} \cdot \left(A_{w_n K_m} \cdot w_n^b \right) \right) \cdot \dot{K}_m^o \right] - \frac{1}{2r} \cdot \sum_{m=1}^{\bar{m}} \left[\left(A_{w_n K_m} \cdot w_n^b \cdot \sigma_{\ln w_n}^2 \right) \cdot \dot{K}_m^o \right] \\
& + \frac{1}{2r} \cdot \sum_{m=1}^{\bar{m}} \left[\left[\sum_{m=1}^{\bar{m}} \left(\frac{\tau_K}{\mu_m} \cdot \left(M_{c_m K_m}^{-1} \cdot c_m \cdot \sigma_{\ln c_m}^2 \right) \cdot \frac{M_{c_m K_m}}{c_m} \cdot \left(A_{w_n K_m} \cdot w_n^b \right) \right) \right] \cdot \dot{K}_m^o \right] \Bigg\}
\end{aligned}
\tag{38}
$$

where $\sum_{m'=1,m'\neq m}^{\bar{m}} \dot{K}_{m'}^{b}$ represents the shadow net investment demand for quasi-fixed inputs other than m. Due to deriving Ω^{b} with respect to factor prices and quasi-fixed factor level (cf. equation (33)) the variances of the (logarithmic) input price—given by $\sigma_{\ln c_m}^{2}$ and $\sigma_{\ln w_n}^{2}$—appear as explanatory variables.

Finally, the optimized observable demand for the numeraire variable input (35) in terms of the value function (36) is given by

$$
\begin{aligned}
x_1^o = \tau_x \cdot r \Bigg\{ & a_0 + \sum_{m=1}^{\bar{m}} \left(b_{K_m} \cdot K_m \right) + b_y \cdot \ln y + \sum_{n=2}^{\bar{n}} \left(b_{w_n} \cdot \ln w_n^b \right) + \sum_{m=1}^{\bar{m}} \left(b_{c_m} \cdot \ln c_m \right) \\
& + \frac{1}{2} \cdot \sum_{m=1}^{\bar{m}} \left(\sum_{m=1}^{\bar{m}} K_m \cdot A_{K_m K_m} \cdot K_m \right) + \sum_{m=1}^{\bar{m}} K_m \cdot A_{yK_m} \cdot \ln y + \frac{1}{2} \cdot \ln y \cdot A_{yy} \cdot \ln y \\
& + \sum_{n=2}^{\bar{n}} \ln y \cdot A_{w_n y} \cdot \ln w_n^b + \frac{1}{2} \cdot \sum_{n=2}^{\bar{n}} \left(\sum_{n=2}^{\bar{n}} \ln w_n^b \cdot A_{w_n w_n} \cdot \ln w_n^b \right) + \sum_{m=1}^{\bar{m}} \ln y \cdot A_{c_m y} \cdot \ln c_m \\
& + \sum_{n=2}^{\bar{n}} \left(\sum_{m=1}^{\bar{m}} \ln w_n^b \cdot A_{c_m w_n} \cdot \ln c_m \right) + \frac{1}{2} \cdot \sum_{m=1}^{\bar{m}} \left(\sum_{m=1}^{\bar{m}} \ln c_m \cdot A_{c_m c_m} \cdot \ln c_m \right) \\
& + \sum_{m=1}^{\bar{m}} \left(\sum_{m=1}^{\bar{m}} c_m \cdot M_{c_m K_m}^{-1} \cdot K_m \right) + \sum_{n=2}^{\bar{n}} \left(\sum_{m=1}^{\bar{m}} w_n^b \cdot A_{w_n K_m} \cdot K_m \right) \Bigg\} \\
& - \tau_x \sum_{n=2}^{\bar{n}} \left(w_n^b \cdot \frac{x_n^o}{\tau_{x_n}} \right) - \tau_x \cdot \sum_{m=1}^{\bar{m}} \left(c_m \cdot K_m \right) - \tau_x \cdot \sum_{m} \Bigg\{ \Bigg(b_{K_m} + \sum_{m=1}^{\bar{m}} \left(A_{K_m K_m} \cdot K_m \right) \\
& + A_{yK_m} \cdot \ln y + \sum_{m=1}^{\bar{m}} \left(M_{c_m K_m}^{-1} \cdot c_m \right) + \sum_{n=2}^{\bar{n}} \left(A_{w_n K_m} \cdot w_n^b \right) \Bigg) \cdot \frac{\dot{K}_m^o}{\tau_{K_m}} \Bigg\} \\
& - \tau_x \cdot \frac{1}{2} \cdot \Bigg[A_{yy} \cdot \sigma_{\ln y}^2 + 2 \cdot \sum_{n=2}^{\bar{n}} A_{w_n y} \cdot \sigma_{\ln w_n, \ln y} + 2 \cdot \sum_{m=1}^{\bar{m}} A_{c_m y} \cdot \sigma_{\ln c_m, \ln y} \\
& + \sum_{n=2}^{\bar{n}} \left(A_{w_n w_n} \cdot \sigma_{\ln w_n}^2 + \sum_{m=1}^{\bar{m}} \left(A_{w_n K_m} \cdot K_m \right) \cdot w_n^b \cdot \sigma_{\ln w_n}^2 \right) + \sum_{n=2}^{\bar{n}} \left(\sum_{m=1}^{\bar{m}} A_{c_m w_n} \cdot \sigma_{\ln c_m, \ln w_n} \right) \\
& + \sum_{m=1}^{\bar{m}} \left(\sum_{n=2}^{\bar{n}} A_{c_m w_n} \cdot \sigma_{\ln c_m, \ln w_n} \right) + \sum_{m=1}^{\bar{m}} \left(A_{c_m c_m} \cdot \sigma_{\ln c_m}^2 + \sum_{m=1}^{\bar{m}} \left(M_{c_m K_m}^{-1} \cdot K_m \right) \cdot c_m \cdot \sigma_{\ln c_m}^2 \right) \Bigg].
\end{aligned}
\tag{39}
$$

Therein $\sigma_{\ln y}^{2}$ represents the variance of the logarithmic output, $\sigma_{\ln w_n, \ln y}$ and $\sigma_{\ln c_m, \ln y}$ denote covariances of the output and input prices. $\sigma_{\ln c_m, \ln w_n}$ represents the covariance of the quasi-fixed and variable input prices.

4.3 Hypotheses

The relevance of factor price and output-level uncertainty is revealed by equations (37)–(39) wherein uncertainty affects the optimal factor demand equations by appearing as an explanatory variable. In the net investment demand equation (37), on the one hand, the negative sign of the last term indicates that uncertainty will reduce investments in the quasi-fixed factor. A negative investment-uncertainty relationship was validated for example by Pietola and Myers (2000) and Hinrichs et al. (2008). Furthermore, the interaction between uncertainty of the quasi-fixed factor price $\sigma^2_{\ln c_m}$ and the quasi-fixed factor level K_m indicates that the effect of uncertainty on investment may differ depending on the level of K_m.

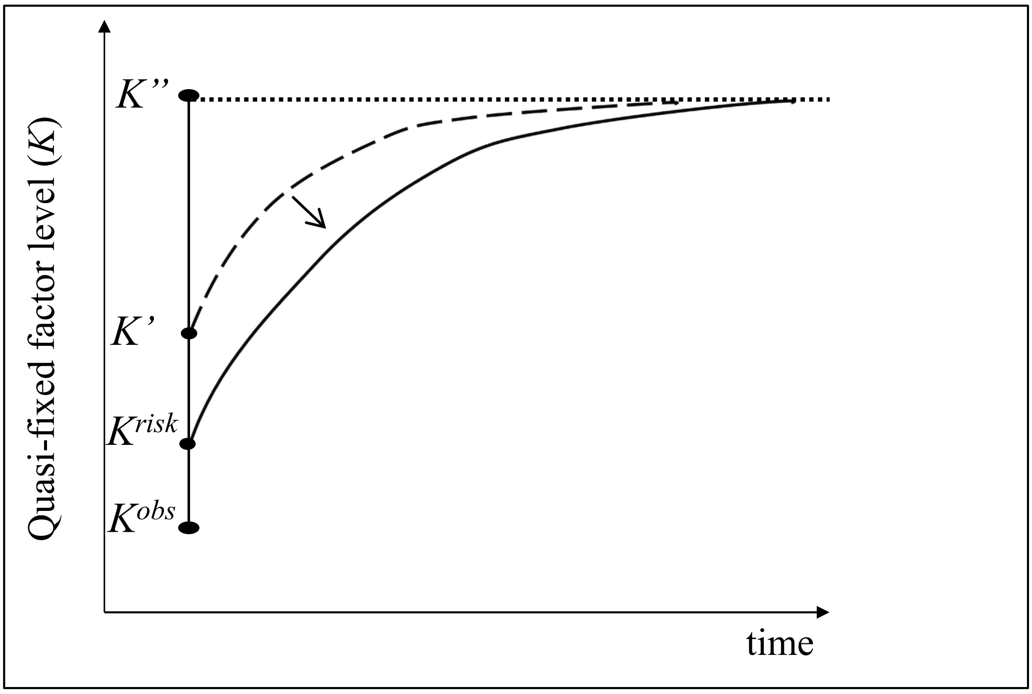
On the other hand, the impact of uncertainty on the estimates of technical and allocative efficiency is not clear. If uncertainty is ignored this may lead to an omitted variable bias affecting the parameter and efficiency estimates. The bias depends, among others, on the magnitude of the effect of uncertainty on net investment demand and on the correlation between the excluded and the included variables (Clarke 2005). One conjecture might be that inefficiency will be overestimated—due to the observed capital stock being mistakenly examined as to small if the optimal speed of adjustment is overestimated. This view is presented in Figure 15. K^{obs} represents an observation of the quasi-fixed input (K) of a firm at a particular time period.[23] The optimal adjustment of the quasi-fixed input over time is denoted by the curve starting at K'. K'' represents the long-term optimal value of the quasi-fixed input. Uncertainty may increase the reluctance to invest and hence, the optimal adjustment path shifts downwards starting from K^{risk}. The estimated efficiency scores may differ, since the optimal adjustment path and in turn the reference point for the efficiency measurement, K^{risk} and K', differ.

The variable factor demand equations (38) and (39) reveal that different sources of uncertainty play a role for the variable factor demand: variance of quasi-fixed input price, variable input prices and output. For example, the effect of $\sigma^2_{\ln w_n}$ on the factor demand in equation (38) is negative if net investment is zero or positive. The effect of $\sigma^2_{\ln c_m}$ is indeterminate. It appears in two interactions having both a positive and a negative impact on the variable factor demand. The magnitude of the net effect of $\sigma^2_{\ln c_m}$ depends on the respective parameters $M_{c_m K_m}$ and $A_{w_n K_m}$. Equation (39) indicates that for example the variance of the logarithmic output has a negative impact on the variable factor demand depending on the sign of the covariance. The

23 The time index is left out in the figure for illustrating purposes.

relevance and magnitude of the covariance has to be defined empirically. In addition, the effect is scaled by the technical inefficiency parameter τ_x. From this background, it is difficult to assess the net effect of uncertainty on the factor demand. Again, ignoring uncertainty may lead to an omitted variable bias which might be transmitted to inaccurate technical and allocative efficiency scores of variable factors and net investment.

Figure 15. Asset fixity, uncertainty and efficiency



Source: Adapted based on Gardebroek and Oude Lansink (2008).

5 Empirical implementation for West German dairy farms

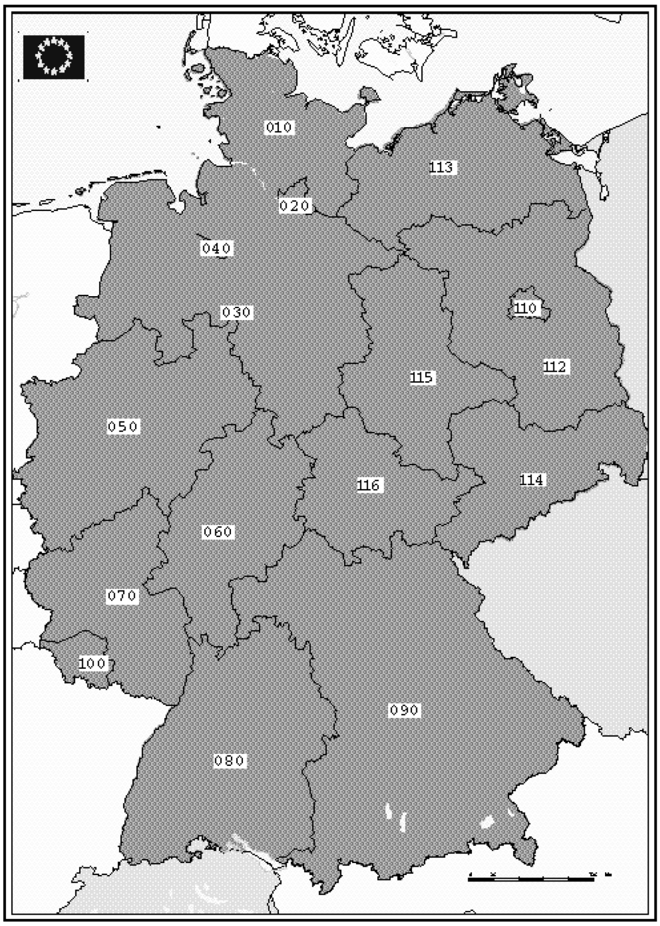
In the following chapter the empirical implementation of the dynamic efficiency model under uncertainty is presented. First, the data set and the variable definition are explained in addition to descriptive statistics (5.1). Second, the empirical model for one output, one quasi-fixed and two variable inputs is defined (5.2). This includes the specific form of the value function, the input demand in terms of the value function parameters, the empirical counterparts and the specification of the efficiency parameters all leading to the empirical system of equations to be estimated. Third, the estimation procedure for the non-linear recursive system of equations is presented (5.3).

5.1 Data and variable description

5.1.1 Data base and farm selection

The data for German dairy farms are drawn from the national farm accountancy data network —henceforth BMEL-Testbetriebsnetz. The BMEL-Testbetriebsnetz is part of the EU FADN used to evaluate farms' economic performance and to prepare and evaluate policy instruments at the national and EU level (BMEL 2014b). The FADN was established in 1965 and consists of accountancy data to determine the income and to analyze farms' business. The FADN consists of annual surveys from a sample of agricultural holdings in the EU. The annual sample covers approximately 80,000 holdings whereby representing about 6.4 million farms in the EU-27 member states. This accounts for 90% of the total agricultural production of the EU. The data collection is at the responsibility of a liaison agency in each member state. In Germany the liaison agency is the Johann Heinrich von Thünen-Institut (European Commission 2010b). The accountancy of the representative selected farms (in German: *Testbetriebe*) is based on standardized rules for the year-end closing. The data are not publicly available. Figure 16 depicts the 16 FADN regions in Germany. The West German federal states are represented by code 010–100—e.g., Schleswig-Holstein is denoted by code 010, North Rhine-Westphalia is denoted by 050 and 090 denotes Bavaria—and the East German federal states are represented by code 110–116—e.g., code 112 refers to Brandenburg (European Commission 2012a).

Figure 16. FADN regions in Germany



Source: European Commission (2012a).

From the raw data a subsample covering the years 1996 until 2010 is selected and farms related to gardening, vinery and fishery are removed from the data set. To relate the expenditures directly to dairy activities, specialized dairy farms where more than 75% of the total revenues are realized from dairy production are chosen and Table 2 depicts examples for selection criteria for specialized dairy farms in the efficiency literature. The empirical analysis is conducted for farms in West Germany since specialized dairy farms are concentrated in West Germany; in East Germany most farms are mixed farms. In addition, farms must be present at least 5 years in the panel. Following Mosheim and Lovell (2009), incomplete observations are ignored and for consistency reasons values below and above the 1st and 99th percentile are ignored and the milk yield per cow and year is restricted to ≥ 3.0 tons to increase homogeneity among the farms (e.g., Mendes et al. 2013). Furthermore, only farms with at least one observation in time with positive investment rates are considered. Hence, observations with zero or negative investments were excluded from the data set. As a result, the employed data set is unbalanced, with 4,201 observations.

Table 2. Examples of selection criteria for specialized dairy farms

Country	Authors	Selection criteria
DE	Abdulai and Tietje (2007)	≥ 75% of total revenue from dairy production
DE	Brümmer et al. (2002)	≥ 75% of total standardized gross margin from dairy production
ES	Alvarez and del Corral (2010)	≥ 90% of farm income from dairy production
ES	Alvarez et al. (2006)	≥ 90% of farm income from dairy production
IT	Pierani and Rizzi (2003)	≥ 75% of total revenue from dairy production
NL	Serra et al. (2011)	≥ 80% of farm income from dairy production
U.S.	Silva and Stefanou (2003; 2007)	≥ 80% of total revenue from dairy production

Note: The countries are abbreviated according to ISO 3166-2: DE: Germany, ES: Spain, IT: Italy, NL: Netherlands and U.S.: United States of America.

5.1.2 Output, quasi-fixed and variable inputs

One output (y_{it}) is defined as milk production per farm in metric tons since the farms in the data set are highly specialized. This is in line with the literature, e.g., Alvarez and Arias (2004) or Alvarez and del Corral (2010). Milk production per farm is calculated by multiplying the individual milk yield per cow by the number of cows per farm.

To keep the empirical equations to a manageable size and to reduce the complexity of the model, one quasi-fixed input (K_{it}) is defined as livestock capital given by the number of cows per farm. The number of cows is used as a proxy for the stock of quasi-fixed inputs and the scale of the farm since a positive correlation between number of dairy cows and buildings, equipment and labor exists in the sample (cf. Adelaja 1991; Quiroga and Bravo-Ureta 1992). Following Quiroga and Bravo-Ureta (1992), the annual price for livestock capital is defined as $c_{it} = \left(0.5 p_{it}^{dc} + 0.5 p_{(i)t}^{cc}\right) h_t + (p_{it}^{dc} - p_{(i)t}^{cc}) / li$, where p_{it}^{dc} denotes the price per dairy cow directly taken from the data base and $p_{(i)t}^{cc}$ describes the price per culled cow.[24] Symbol h_t denotes the interest rate proxied by the average yearly deposit rate of interest provided by the Deutsche Bundesbank (cf. Appendix B, Table 14), and li refers to an approximate three-year useful life of a dairy cow (BMELV 2009). The first term reflects the opportunity costs of capital for holding a cow and the second term represents average depreciation. Net investment in the quasi-

[24] Due to data limitations on the farm level, regional prices for this variable, indicated by (i), are resorted. The prices per culled cow are presented in Appendix B, Table 13.

fixed factor I_{it}—empirical equivalent to $\dot{K}$—is calculated at the farm-level by using $\left(K_{it} - K_{i,t-1}\right) / K_{i,t-1}$.

Two variable inputs are defined: purchased feed ($x_{2,it}$) and other inputs ($x_{1,it}$) where the latter serve as the numeraire. Purchased feed, being a crucial production factor in dairy production, consists of purchased concentrates and roughage. Since no information about the respectively used quantity of purchased feed is available in the data set the implicit quantity is calculated using the ratio of the farm's expenditures for purchased feed concentrates and roughage to the yearly feed price index ($w_{2,t}$) provided by Statistisches Bundesamt (2013b). Other inputs consist of insemination, veterinary service, inputs for roughage production—seeds, fertilizer, and pesticides—hired labor and energy—containing heating, electricity, fuel and fuel refund. The respective quantity is defined as the ratio of the aggregated farm expenditures to the price index for those inputs ($w_{1,it}$) based on the Törnqvist price index where either prices at the farm level or price indices from official statistics (Statistisches Bundesamt 2013b) depending on the availability at the farm level are used.[25] In reality, output is affected by a variety of inputs. However, data limitations prevent the author to use more inputs such as genetic quality or animal welfare (cf. Stokes et al. 2007).

Summary statistics of the main variables are given in Table 3. On average, the revenue from milk production of the sample farms amounts to 87,832.94 Euros per year. The average expenditures for purchased feed amount to 14,409.95 Euros per year and 19,598.64 Euros are spent for the other input category. The average farm size amounts to 49.57 hectares. The sample farms produce on average 283.30 tons of milk per farm with 44 cows and the number of cows per farm ranges between 10 and 201.

[25] The farm-level price per insemination was calculated by dividing the farm-level expenditures by the number of inseminations (assumed to be 2.0 according to official statistics). The hourly wage of hired labor was calculated by dividing the farm-level gross wage by the annual labor hours (labor units from the data set were transformed to annual hours by using 2,200 hours per labor unit, e.g., Brümmer et al. (2002)). The prices of veterinary service, seeds, fertilizer, pesticides and energy were taken from Statistisches Bundesamt (2013b).

Table 3. Descriptive statistics of the key variables

Variable		Mean	Standard deviation	Min.	Max.
Milk production per farm y_{it}	[metric tons]	283.30	129.64	50.64	1,613.02
Livestock capital K_{it}	[# of cows]	44	18	10	201
Net investment I_{it}	[ratio]	0.085	0.088	0.02	3.44
Purchased feed $x_{2,it}$	[quantity index]	128.90	61.33	18.14	248.33
Other inputs $x_{1,it}$	[quantity index]	697.73	1,149.06	58.39	12,065.22
Purchased feed price $w_{2,t}$	[price index]	111.78	15.20	95.02	150.90
Price of other input $w_{1,it}$	[price index]	63.03	33.87	2.41	204.84
Capital price c_{it}	[Euros per cow]	60.10	43.41	16.35	1,612.60

Note: Data from BMEL-Testbetriebsnetz, 1996–2010 and Statistisches Bundesamt (2013b). N=4,201.

The respective percentiles—calculated by ordering the values from lowest to highest—of milk production per farm, milk yield per cow, cows per farm (livestock capital) and investment rate are presented in Table 4. The 1st percentile of milk production per farm and of the milk yield per cow is 83.71 tons per year and 3.97 tons, respectively. The median (50th percentile) of milk production per farm is equal to 266.05 tons; the median of the milk yield per cow is equal to 6.36 tons. The 1st percentile of livestock capital—measured in dairy cows per farm—is equal to 15.4 cows and the median is 41.5 cows. The investment rate at the farm level has a median of 0.064 and the lowest percentile is 0.021.

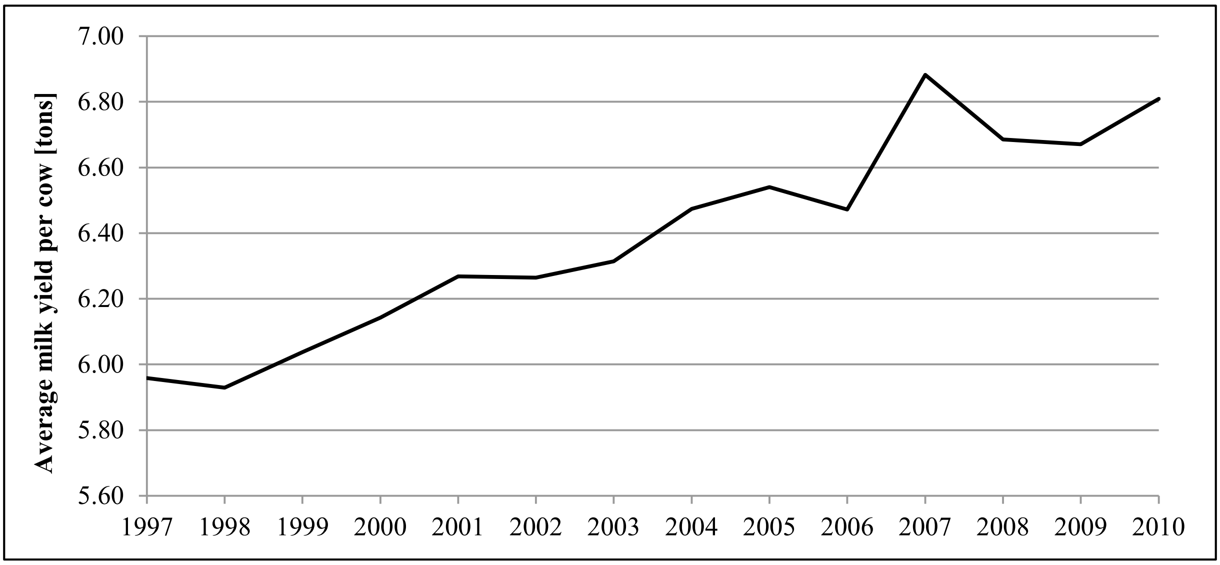
Table 4. Percentiles of milk and livestock variables

Percentile	Milk production per farm [metric tons]	Milk yield [metric tons per cow, year]	Dairy cows per farm	Investment rate
1st	83.71	3.97	15.4	0.021
5th	119.72	4.64	21	0.024
10th	142.35	5.02	24.5	0.027
25th	190.03	5.63	31.5	0.038
50th	266.05	6.36	41.5	0.064
75th	355.53	7.11	53.6	0.107
90th	441.02	7.80	66.5	0.165
99th	635.87	9.09	96.5	0.352

Source: Own calculations based on BMEL-Testbetriebsnetz, 1996–2010.

The development of the milk yield per cow is reported in Figure 17. Even though the panel is unbalanced, inspecting the development over time is worthwhile: Figure 17 confirms the observation made in West Germany (cf. Figure 6) for the sample farms: the average milk yield per cow and year has increased over time from 5.96 tons (1997) to 6.81 tons (2010) with an average of 6.39 tons.

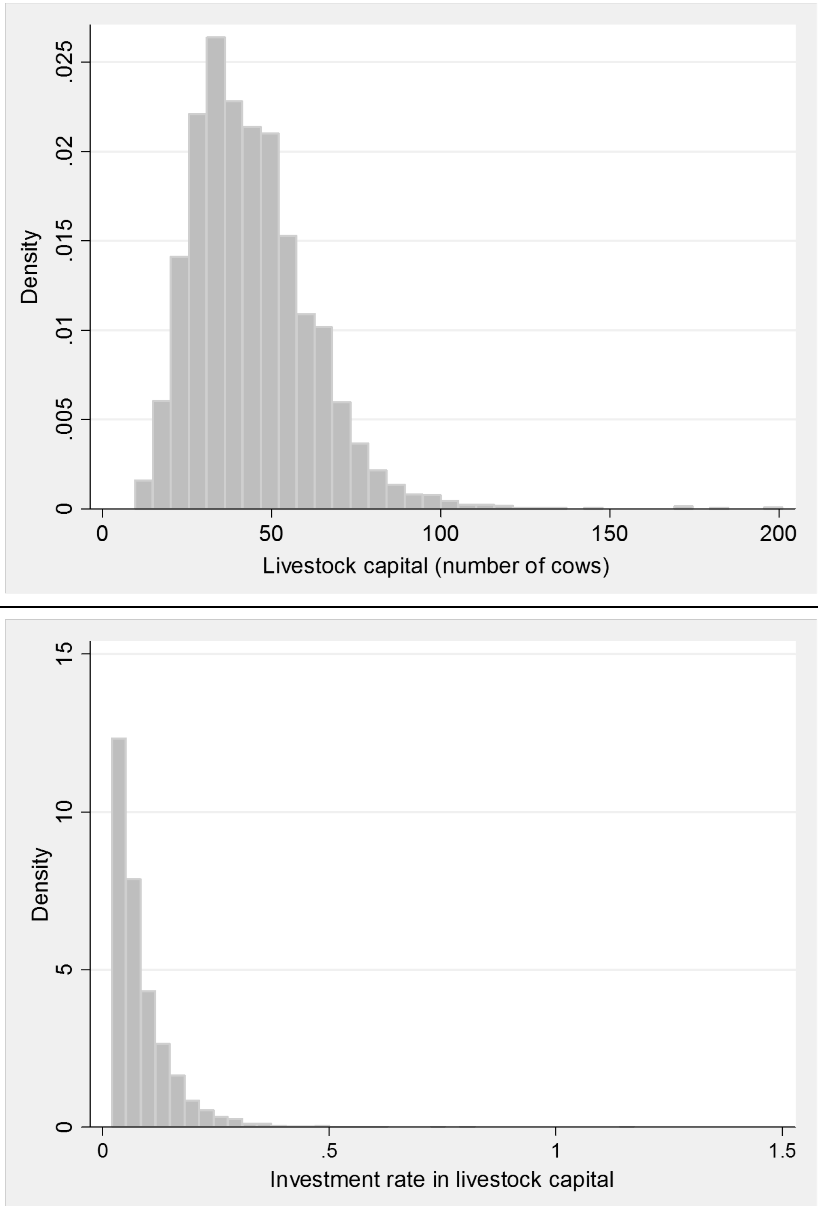
Figure 17. Average milk yield per cow over time



Source: Own calculations based on BMEL-Testbetriebsnetz, 1996–2010.

The histograms of livestock capital and investment in livestock capital are presented in Figure 18. The shape of the histogram for livestock highlights that there exist only a few larger farms (> 100 cows) and a more pronounced left-skewed distribution is observed. The histogram for investment rate of livestock capital shows that the majority is characterized by rather low investment rates where the minimum investment rate is defined to be 0.02. The histograms of the variable input quantities are presented in Appendix B, Figure 27.

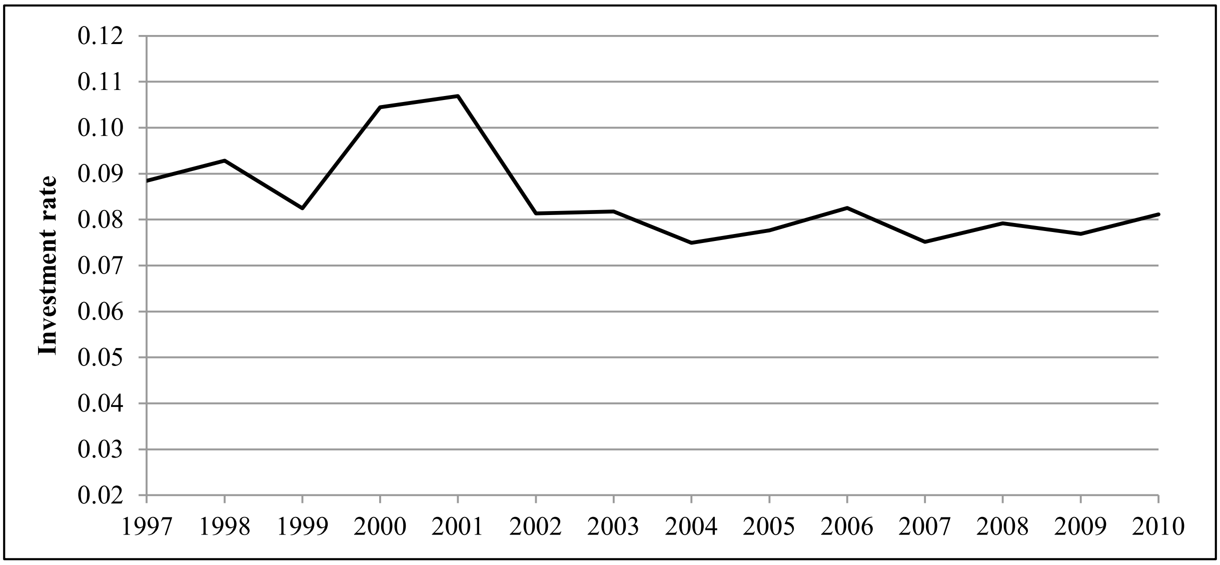
Figure 18. Histogram of livestock capital and investment rate



Source: Own calculations based on BMEL-Testbetriebsnetz, 1996–2010.

Figure 19 shows the development of the investment rate over time. The highest average investment rate has been observed in 2001 (0.107) and the lowest investment rate in 2004 (0.075). The investment rate slightly decreased between 1997 and 2010. A study conducted by Sauer and Latacz-Lohmann (2014) report decreasing investment rates for German dairy farms between 2006 and 2008.

Figure 19. Average investment rate over time



Source: Own calculations based on BMEL-Testbetriebsnetz, 1996–2010.

5.1.3 Price and output-level uncertainty

The theoretical model accounts for output-level and price uncertainty and uncertainty enters the empirical model through three variables: uncertainty of the output level (y_{it}), of the price process for purchased feed ($\ln w_{2,it}$) and the natural logarithm of the quasi-fixed factor price process ($\ln c_{it}$).[26]

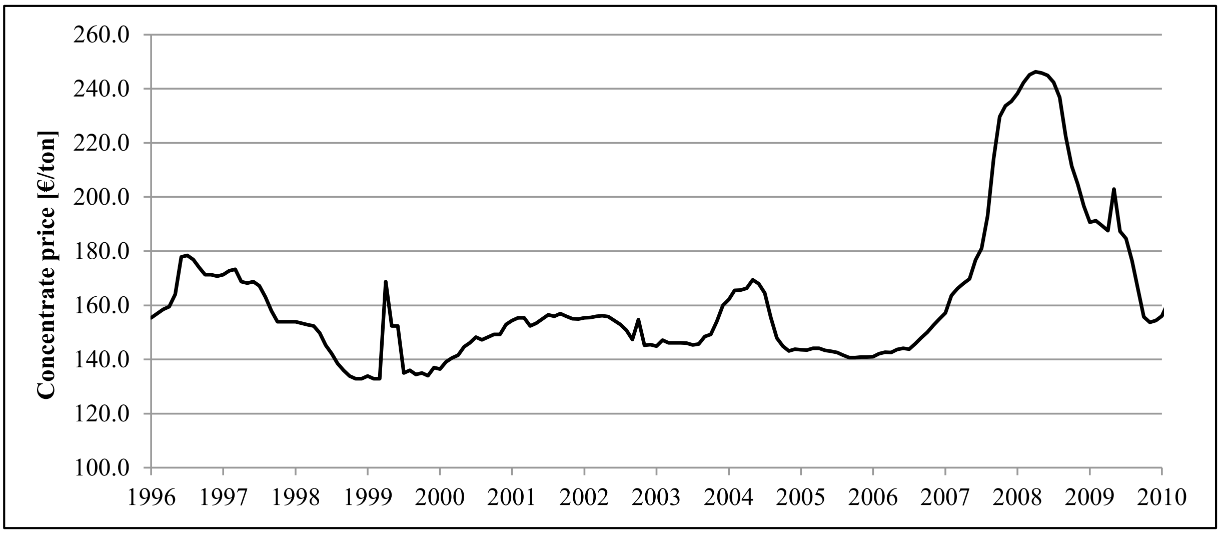
Output volatility $\sigma^2_{\ln y,i}$ is measured by the variance of the farm-specific milk production. In the data set, milk output is only available with a short time series dimension, which does not permit the author to calculate a time-varying volatility. Since milk production levels and their volatility differ by farm due to unobserved production conditions like feed quality, soil quality or weather conditions, this measure of output uncertainty constitutes a reasonable proxy.

A farm- and time-specific measure for the feed price volatility would require farm-specific purchase prices; however, only information on feed concentrate expenditures is available without any quantity information. Hence, the volatility measure $\sigma^2_{\ln w_2,t}$ is calculated from a time series for feed concentrates for Germany and the development in the period under consideration (1996–2010) is presented in Figure 20. Between 1996 and middle of the year 2006 the price ranged between 130 and 180 Euros per ton. In the following months, the prices steeply

[26] Note that uncertainty of the first variable input price does not enter the model since it is the numeraire.

increased up to 246 Euros per ton in April 2008 followed again by a decline to 153 Euros per ton in November 2009.

Figure 20. Monthly prices of feed concentrates in Germany



Source: ZMP, AMI (diverse volumes).

To measure the respective time-varying price volatility a generalized autoregressive conditional heteroscedasticity (GARCH) model is used (e.g., Boetel et al. 2007). The GARCH model is a univariate volatility model and dates back to Bollerslev (1986). The procedure to obtain the feed price volatility involves three major steps described in the following. First, an augmented Dickey-Fuller (ADF) test is performed to test whether the time series has a unit-root. The null hypothesis states that the price series contains a unit root and is non-stationary whereas the alternative hypothesis states that the price series does not contain a unit root and is stationary (Greene 2003). The ADF test confirms that the null hypothesis of a unit root cannot be rejected for the time series—test statistic -1.194 and p-value 0.676. That is, the times series is non-stationary in levels, however, the series is tested to be stationary in the returns—test statistic 7.824 and p-value 0.000—and the monthly returns are calculated as the difference between logarithmic prices of two month. The development as reported in Figure 21 states that positive and negative returns exist. The returns are negative (positive) if the price in the current month is lower (higher) than in the previous month. Negative returns are observed in 44% of the cases.

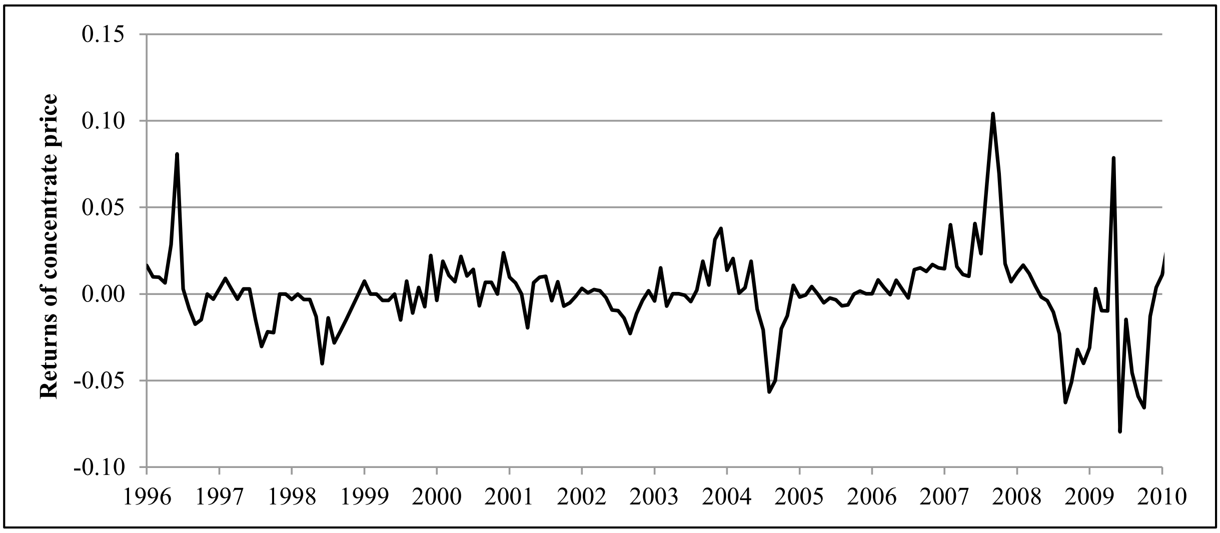
Second, the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the returns, crucial for estimating a time series model, are obtained. The ACF describes the correlation between the observed data point and its lagged values. From the ACF it is difficult to identify the order of a time series process and the PACF is used in addition (Verbeek 2000).

These functions are depicted in Figure 22 suggesting that the monthly returns are not independent. Based on the ACF and PACF, the author constructs different econometric models for the time series of the feed concentrate returns using Stata11 computer software. The Akaike information criterion (AIC)—dating back to Akaike (1974)—is used to evaluate the model fit and the AIC is defined as $\mathrm{AIC} = \left(-2\ln L + 2k\right)$ where $\ln L$ denotes the log-likelihood of the model and k is the number of parameters estimated. A related model fit criterion is the Schwarz's Bayesian information criterion (BIC) defined as $\mathrm{BIC} = \left(-2\ln L + \ln N \cdot k\right)$ where N is the number of observations (cf. Schwarz 1978). A model with smaller AIC (BIC) is superior to a model with higher AIC (BIC) values (cf. Verbeek 2000; Greene 2003). Even though several time series models have been built, the best model fit has been obtained by an autoregressive (AR) process of order one (AR(1)) combined with a moving average (MA) component of order two and nine (MA(2,9)).

Third, the residual series of the model is used to test for autoregressive conditional heteroscedasticity; that is, ARCH effects. The Engle's Lagrange-multiplier test indicates that ARCH effects exist. Using the AIC and BIC, a GARCH(1,1) is specified where the ARCH and GARCH parameters are found to be statistically significant different from zero. Specifying the correct order is challenging, hence, lower order GARCH models for example GARCH(1,1), GARCH(2,1), and GARCH(1,2) are commonly used in empirical applications (Tsay 2002). Subsequently, the conditional[27] variance of feed concentrate price is predicted (Figure 23). The conditional variance depends on the squared error term in the previous period—denoted as the ARCH term—and on the conditional variance in the previous time period—denoted as the GARCH term. The variance is used as a variable that enters the empirical factor demand functions.

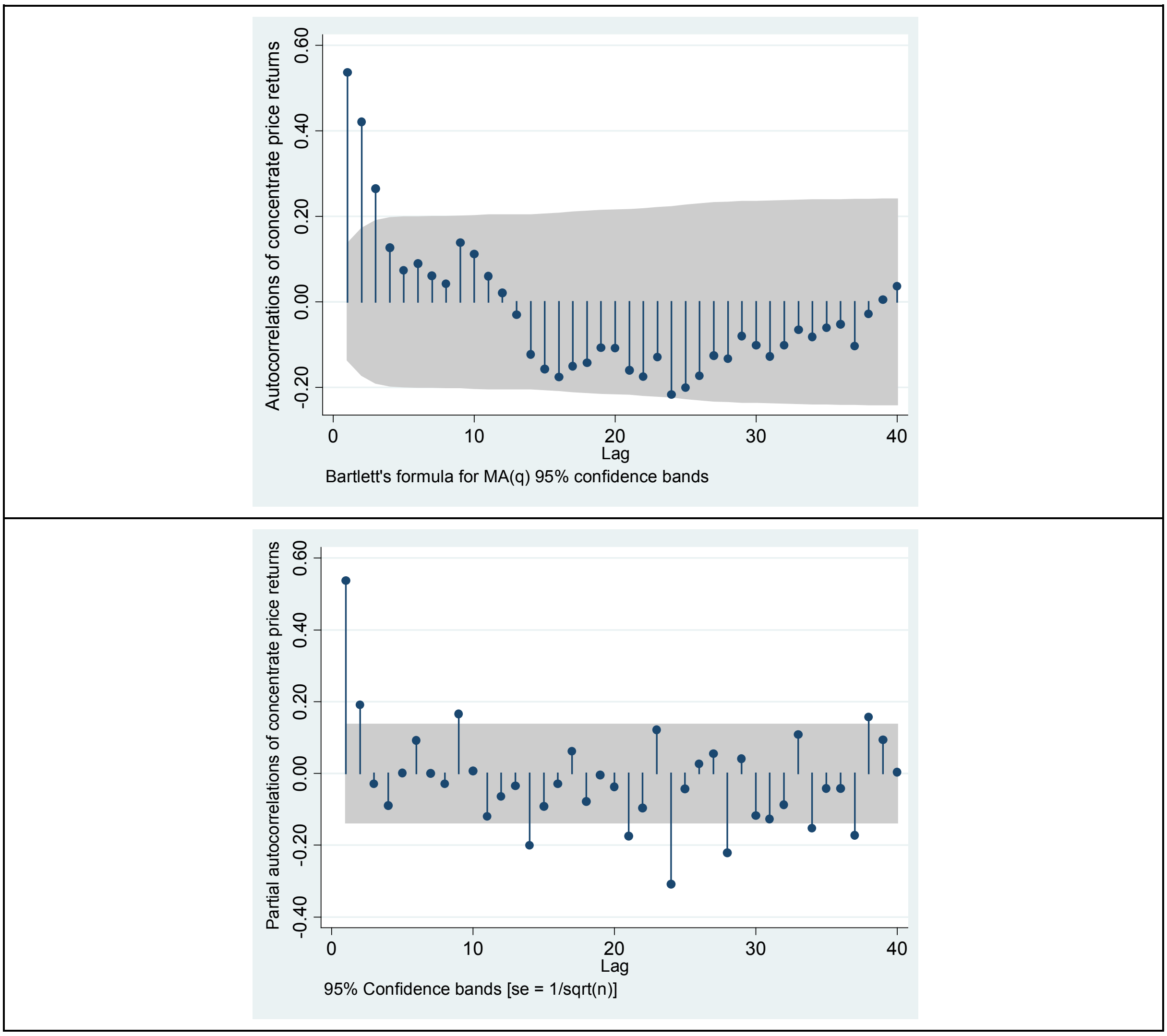
[27] The term "conditional" implies that the variance model imposed by GARCH explicitly depend on past observations being the key insight of GARCH.

Figure 21. Returns of feed concentrate price



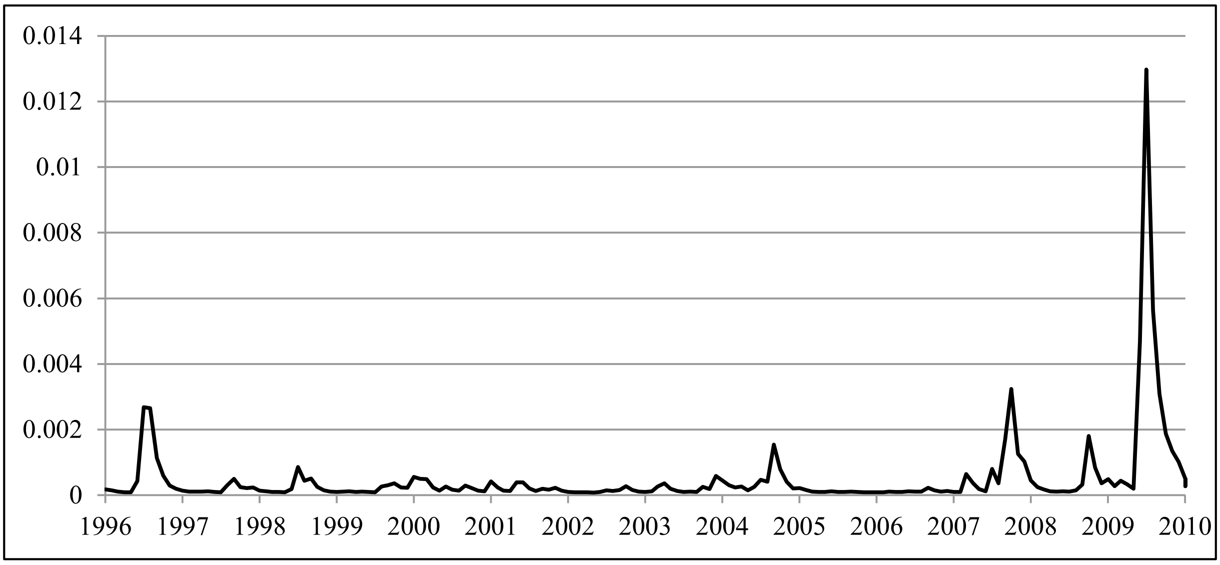
Source: Own calculations.

Figure 22. ACF and PACF of feed concentrate price returns



Source: Own calculations.

Figure 23. Conditional variance of feed concentrate price

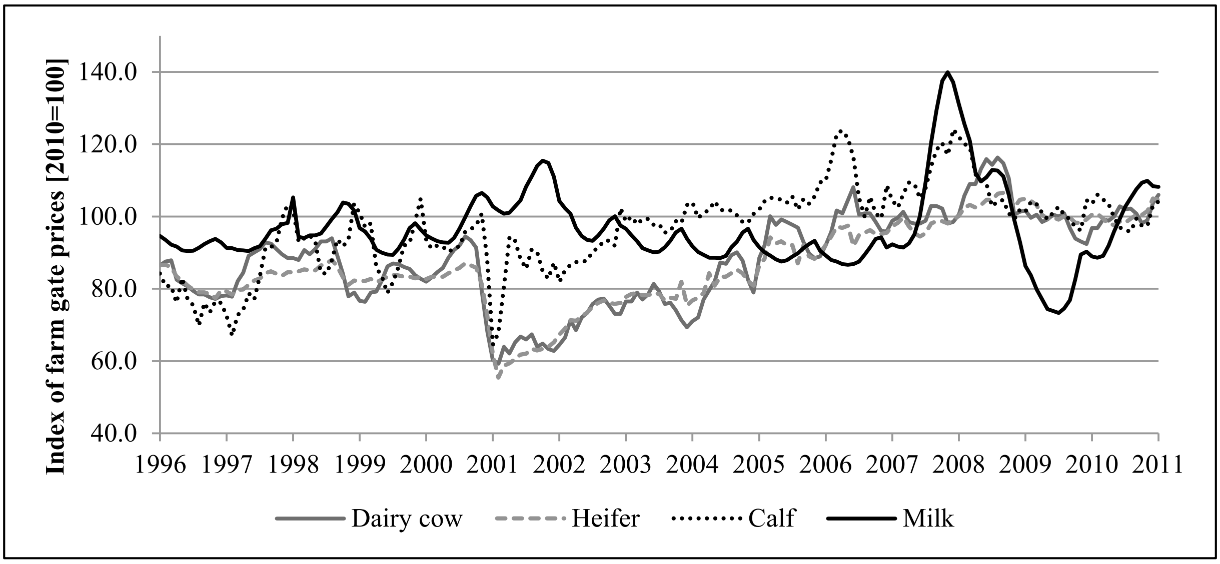


Source: Own calculations.

The uncertainty of the quasi-fixed factor price $\sigma^2_{\ln c}$ is difficult to quantify. Given that only bookkeeping values of livestock are available in the data set, but milk and livestock prices are highly correlated (cf. Figure 24), this variable is proxied by the variance of the farm-specific milk price. This individual measure is reasonable because different farm-specific conditions like feed quality, soil quality or weather might influence the milk quality and the respective milk price. This measure, however, does so far not reflect the substantial changes in milk price volatility in the years 1997–2010 (cf. Figure 24). Fundamental changes in the EU CAP such as the reduction of market intervention and decoupling of direct payments (cf. section 2.1), accompanied with an increase of the total milk quota quantity lead to a significant increase in the volatility of commodity prices from 2005 on (cf. Keane and O'Connor 2009; Jongeneel et al. 2010). Thus, to capture this development two volatility regimes are defined: a low- (1997–2004) and a high-volatility regime (2005–2010).[28] Indeed, the coefficient of variation of the milk price increases between the two periods indicating an increased dispersion of prices and supports the two regimes. Covariances of the stochastic variables, for instance between the livestock capital and the feed price, are found to be low and are thus neglected in the empirical analysis.

[28] Symbol $\sigma^2_{\ln c,it}$ for the volatility measure is indexed by *i* and *t* where the time index *t* indicates each volatility regime: 1997–2004 and 2005–2010.

Figure 24. Farm gate price indices for dairy cows, heifers, calves and milk in Germany



Source: Statistisches Bundesamt (2013a).

5.2 Empirical model

The factor demand equations (37)–(39) are simplified to reduce the complexity of the empirical model. For this, the model dimension is confined to one quasi-fixed input, two variable inputs, and one output and the shadow value function (36) is given by

$$\begin{aligned} J^b(z,K) &= a_0 + b_K \cdot K + b_y \cdot \ln y + b_{w_2} \cdot \ln w_2^b + b_c \cdot \ln c + A_{KK} \cdot \frac{1}{2} K^2 + A_{yK} \cdot K \cdot \ln y \\ &\quad + A_{yy} \cdot \frac{1}{2}(\ln y)^2 + A_{w_2 y} \cdot \ln y \cdot \ln w_2^b + A_{w_2 w_2} \cdot \frac{1}{2}\left(\ln w_2^b\right)^2 + A_{cy} \cdot \ln y \cdot \ln c \\ &\quad + A_{cw_2} \cdot \ln w_2^b \cdot \ln c + A_{cc} \cdot \frac{1}{2}(\ln c)^2 + M_{cK}^{-1} \cdot c \cdot K + A_{w_2 K} \cdot w_2^b \cdot K \end{aligned} \tag{40}$$

where a_0 is an unknown constant term and the b-parameters represent first-order parameters, A- and M-parameters represent second-order parameters of the value function. The last term ($M_{cK}^{-1} \cdot c \cdot K + A_{w_2 K} \cdot w_2^b \cdot K$) enters the shadow value function—in contrast to non-stochastic models—to ensure that J_z^b is quadratic and J_{zz}^b is linear in *w* and *c* (cf. section 4.2). The shadow price of the second input w_2^b is defined as $w_2^b = (\lambda_2 w_2 / \lambda_1 w_1) = \lambda_{21} w_{21}$.

Accordingly, the net investment demand in (37) in terms of the value function parameters is given by

$$\dot{K} = \tau_K \left[\left(M_{cK} r \left(\left(b_c + A_{cw_2} \ln \lambda_{21} \right) \cdot \frac{1}{c} + A_{cy} \cdot \frac{1}{c} \ln y + A_{cw_2} \cdot \frac{1}{c} \ln w_{21} + A_{cc} \cdot \frac{1}{c} \ln c \right) \right. \right. \\ \left. + \left(r - M_{cK} \right) \cdot K - \frac{1}{2} \cdot \sigma_{\ln c}^2 K \right] \tag{41}$$

and the demand for the variable inputs in equations (38) and (39) in terms of the value function parameters are given by

$$\begin{aligned} x_2 = \frac{1}{\mu} \Bigg[& \tau_K \Bigg(A_{cw_2} r \cdot \frac{1}{w_{21}} + \left(A_{w_2 K} \lambda_{21} r - M_{cK} A_{w_2 K} \lambda_{21} \right) \cdot K + A_{w_2 K} \lambda_{21} M_{cK} A_{cy} r \cdot \ln y \cdot \frac{1}{c} \\ & + \left(b_c A_{w_2 K} + A_{w_2 K} \ln \lambda_{21} A_{cw_2} + A_{cw_2} A_{w_2 K} \right) \lambda_{21} M_{cK} r \cdot \frac{1}{c} + A_{KK} M_{cK} A_{cw_2} r \cdot K \frac{1}{w_{21}} \frac{1}{c} \\ & + A_{w_2 K} \lambda_{21} M_{cK} A_{cc} r \cdot \ln c \frac{1}{c} + b_K M_{cK} A_{cw_2} r \cdot \frac{1}{w_{21}} \frac{1}{c} + A_{w_2 K} \lambda_{21} M_{cK} A_{cw_2} r \cdot \ln w_{21} \frac{1}{c} \\ & + A_{yK} M_{cK} A_{cw_2} r \cdot \ln y \frac{1}{w_{21}} \frac{1}{c} + \left(A_{w_2 K} \lambda_{21} \cdot M_{cK} \frac{1}{r} - A_{w_2 K} \lambda_{21} \right) \cdot \dot{K} - A_{w_2 K} \lambda_{21} \frac{1}{2} \cdot K \sigma_{\ln c}^2 \\ & - A_{KK} M_{cK} A_{cw_2} \cdot \dot{K} \frac{1}{w_{21}} \frac{1}{c} + A_{w_2 K} \lambda_{21} \frac{1}{2r} \cdot \dot{K} \sigma_{\ln c}^2 \Bigg) \Bigg] - \tau_x A_{w_2 K} \frac{1}{2} \cdot K \sigma_{\ln w_2}^2 \\ & + r \left(A_{w_2 w_2} \frac{\tau_x}{\lambda_{21}} \cdot \frac{1}{w_{21}} + \tau_x A_{w_2 K} r \cdot K - \tau_x A_{w_2 K} M_{cK} A_{cw_2} \cdot \frac{1}{c} \right) - A_{w_2 K} \lambda_{21} \frac{1}{2r} \cdot \dot{K} \sigma_{\ln w_2}^2 \end{aligned} \tag{42}$$

and

$$\begin{aligned} x_1 = \tau_x \Bigg[& r \cdot \Bigg(a_0 + b_{w_2} \ln \lambda_{21} + A_{w_2 w_2} \frac{1}{2} \left(\ln \lambda_{21} \right)^2 + b_K \cdot K + A_{KK} \frac{1}{2} \cdot K^2 + A_{yK} \cdot \ln y K \\ & + A_{w_2 K} \lambda_{21} \cdot w_{21} K + \left(b_y + A_{w_2 y} \ln \lambda_{21} \right) \cdot \ln y + A_{yy} \frac{1}{2} \cdot \left(\ln y \right)^2 + A_{w_2 y} \cdot \ln y \ln w_{21} \\ & + \left(A_{cw_2} \ln \lambda_{21} + b_c \right) \cdot \ln c + A_{cc} \frac{1}{2} \cdot \left(\ln c \right)^2 + A_{cy} \cdot \ln y \ln c + A_{cw_2} \cdot \ln w_{21} \ln c \\ & + \left(b_{w_2} + A_{w_2 w_2} \ln \lambda_{21} \right) \cdot \ln w_{21} + A_{w_2 w_2} \frac{1}{2} \cdot \left(\ln w_{21} \right)^2 \Bigg) + \left(M_{cK} r - 1 \right) \cdot cK - b_K \frac{1}{\tau_K} \cdot \dot{K} \\ & - \frac{1}{\tau_K} A_{KK} \cdot K \dot{K} - A_{yK} \frac{1}{\tau_K} \cdot \ln y \dot{K} - A_{w_2 K} \lambda_{21} \frac{1}{\tau_K} \cdot w_{21} \dot{K} - M_{cK} \frac{1}{\tau_K} \cdot c \dot{K} \\ & - M_{cK} \frac{1}{2} \cdot K c \sigma_{\ln c}^2 - A_{w_2 K} \lambda_{21} \frac{1}{2} \cdot K w_{21} \sigma_{\ln w_2}^2 - A_{w_2 y} \cdot \sigma_{\ln w_2, \ln y} - A_{cy} \cdot \sigma_{\ln c, \ln y} \\ & - A_{cw_2} \cdot \sigma_{\ln c, \ln w_2} - A_{yy} \frac{1}{2} \cdot \sigma_{\ln y}^2 - A_{w_2 w_2} \frac{1}{2} \cdot \sigma_{\ln w_2}^2 - A_{cc} \frac{1}{2} \cdot \sigma_{\ln c}^2 \Bigg] - \lambda_{21} \cdot w_{21} x_2 . \end{aligned} \tag{43}$$

These equations are the basis for deriving the empirical system of equations. The system is recursive in net investment demand—serving as an explanatory variable in the variable input demand equations. In addition, the system is recursive in the variable input demand x_2 as it is an explanatory variable for the demand of other inputs, x_1. Next, the empirical counterparts for the equations (41)–(43) are derived including three major steps.

First step Estimating equations (41)–(43) would not results in consistent estimates of the value function parameters and efficiency scores because parameters appear in combinations and cannot be disentangled using only a single equation. Hence, these parameters are aggregated and estimated together—e.g., as $\beta_1 = \left(b_c + A_{cw_2} \ln \lambda_{21}\right)$. The estimated coefficients are then used in the subsequent estimation steps. After all three equations are estimated, the structural parameters of the value function are retrieved from the estimated coefficients. Thereby it can be checked whether the value function properties are obeyed by the parameter estimates.

Second step Uncertainty of factor prices enters equation (41) through an interaction term: the variance of the quasi-fixed factor price $\sigma^2_{\ln c}$ interacted with the quasi-fixed factor level K. Referring to Aiken and West (1991) one way of understanding the meaning of an interaction term is to calculate the simple slope—indicating the slope of the regression of $\dot{K}$ on $\sigma^2_{\ln c}$ conditional on different levels of K. From this it becomes apparent, that this evaluation is only possible if both the constitutive terms—$\sigma^2_{\ln c}$ and K—as well as the interaction term—$\sigma^2_{\ln c}K$—are present in the regression equations (e.g., Brambor et al. 2006). Thus, the uncertainty term is further integrated in the demand equations as an explanatory variable even though it is not directly coming from the theoretical model. The main interest is to evaluate the interaction of the quasi-fixed factor price uncertainty times the quasi-fixed factor level—given by $\sigma^2_{\ln c}K$—thus, only $\sigma^2_{\ln c}$ and not all constitutive terms of other interactions—for example the constitutive terms of the interaction $1/c \cdot \ln y$ or $1/c \cdot \ln w_{21}$—are included as additional regressors. The same procedure is applied for the interaction terms in equations (42) and (43). In contrast to former dynamic dual efficiency models the model allows the researcher to identify technical inefficient levels of net investment as given by τ_K. Furthermore, variables that are related to an interaction term are used in mean centered form which indicates rescaling the variable by subtracting its mean (cf. Jaccard and Turrisi 2003). The main advantage is that the mean of each variable is zero and thereby eases the interpretation of the interaction terms (Aiken and West 1991; Jaccard and Turrisi 2003).

Third step The technical and allocative efficiency terms—so far time-invariant and not farm-specific—are specified as functions of variables to accommodate variation of technical and allocative efficiency. Here the researcher relies on the work of Reinhard and Thijssen (2000) and uses three groups of efficiency determinants: management characteristics, intensity and performance of milk production.

Managerial skills are measured by the age of the farmer (age_{it}) and a dummy variable for agricultural education ($d_i^{edu} = 1$ if the farm manager has obtained higher agricultural education and zero otherwise; e.g., Kumbhakar et al. 1991). Motivated by findings from Hallam and Machado (1996) on the relationship between technical efficiency and production intensity, the number of cows per hectare ($inten_{it}$) and herd performance ($yield_{it}$) are included as explanatory variables. The latter reflects farms' efforts in breeding and feed optimization (cf. Weersink et al. 1990; Reinhard and Thijssen 2000; Hansson and Öhlmer 2008). Moreover, a dummy variable for the southern German federal states is introduced ($d_i^{south} = 1$ if the farm is located in southern Germany and zero otherwise) to cover different local factor availability (like land or quota) and site-specific differences in efficiency. Accordingly, technical inefficiency of net investment $\tau_{K,it}$ and of variable factors $\tau_{x,it}$ are modeled using an exponential transformation to ensure non-negative values (cf. Rungsuriyawiboon and Stefanou 2007) as

$$\tau_{K,it} = \left[\exp\left(\omega_1 \cdot d_i^{edu} + \omega_2 \cdot age_{it} + \omega_3 \cdot inten_{it} + \omega_4 \cdot yield_{it} + \omega_5 \cdot d_i^{south}\right)\right]^{-1} \tag{44}$$

and

$$\tau_{x,it} = \left[\exp\left(\omega_6 \cdot d_i^{edu} + \omega_7 \cdot age_{it} + \omega_8 \cdot inten_{it} + \omega_9 \cdot yield_{it} + \omega_{10} \cdot d_i^{south}\right)\right]^{-1}. \tag{45}$$

Allocative efficiency of net investment is likewise modeled using an exponential transformation and is assumed to be a function of education, age and livestock density

$$\mu_{it} = \exp\left(\omega_{11} \cdot d_i^{edu} + \omega_{12} \cdot age_{it} + \omega_{13} \cdot inten_{it}\right) \tag{46}$$

where $\omega_1, \ldots, \omega_{13}$ denote parameters to be estimated. The descriptive statistics of these variables, except dummy variables, are given in Table 5.

Table 5. Efficiency variables

Variable		Mean	Standard deviation	Min.	Max.
Dairy cows per hectare $inten_{it}$	[# of cows per hectare]	0.99	0.32	0.24	2.69
Age age_{it}	[years]	46	10	19	101
Average milk yield $yield_{it}$	[tons per cow, year]	6.39	1.10	3.04	10.97

Source: Own calculations based on BMEL-Testbetriebsnetz, 1996–2010.

(In)efficiency terms as given in equations (44)–(46) replace the respective terms in equations (41)–(43). This yields the empirical system of equations to be estimated given by

$$
\begin{aligned}
I_{it} = & \left[\exp\left(\omega_1 \cdot d_i^{edu} + \omega_2 \cdot age_{it} + \omega_3 \cdot inten_{it} + \omega_4 \cdot yield_{it} + \omega_5 \cdot d_i^{south}\right)\right]^{-1} \cdot \\
& \left[M_{cK} r \cdot \left(\beta_1 \cdot \frac{1}{c_{it}} + A_{cy} \cdot \frac{1}{c_{it}} \ln y_{it} + A_{cw_2} \cdot \frac{1}{c_{it}} \ln w_{21,it} + A_{cc} \cdot \frac{1}{c_{it}} \ln c_{it} \right) \right. \\
& \left. \quad + \left(r - M_{cK}\right) \cdot K_{it} + \beta^I_{\sigma^2_{\ln c,it} K_{it}} \cdot \sigma^2_{\ln c,it} K_{it} \right] + \beta^I_{\sigma^2_{\ln c,it}} \cdot \sigma^2_{\ln c,it} + \beta^I_{year} \cdot year_t
\end{aligned} \tag{47}
$$

$$
\begin{aligned}
x_{2,it} = & \left[\exp\left(\omega_{11} \cdot d_i^{edu} + \omega_{12} \cdot age_{it} + \omega_{13} \cdot inten_{it}\right)\right]^{-1} \cdot \\
& \left[\tau_{K,it} \left[A_{cw_2} r \cdot \frac{1}{w_{21,it}} + \beta_2 \left(\left(r - M_{cK}\right) \cdot K_{it} + \left(\beta_1 + A_{cw_2}\right) M_{cK} r \cdot \frac{1}{c_{it}} \right. \right. \right. \\
& + r M_{cK} A_{cy} \cdot \ln y_{it} \frac{1}{c_{it}} + M_{cK} A_{cc} r \cdot \ln c_{it} \frac{1}{c_{it}} + M_{cK} A_{cw_2} r \cdot \ln w_{21,it} \frac{1}{c_{it}} \\
& \left. + \left(M_{cK} \frac{1}{r} - 1 \right) \cdot I_{it} - \frac{1}{2} \cdot K_{it} \sigma^2_{\ln c,it} + \frac{1}{2r} \cdot I_{it} \sigma^2_{\ln c,it} \right) + b_K M_{cK} A_{cw_2} r \cdot \frac{1}{w_{21,it}} \frac{1}{c_{it}} \\
& + A_{KK} M_{cK} A_{cw_2} r \cdot K_{it} \frac{1}{w_{21,it}} \frac{1}{c_{it}} + A_{yK} M_{cK} A_{cw_2} r \cdot \ln y_{it} \frac{1}{w_{21,it}} \frac{1}{c_{it}} \\
& \left. \left. - A_{KK} M_{cK} A_{cw_2} \cdot I_{it} \frac{1}{w_{21,it}} \frac{1}{c_{it}} \right] \right] - \beta_3 \frac{1}{2} \cdot K_{it} \sigma^2_{\ln w_2,t} - \beta_2 \frac{1}{2r} \cdot I_{it} \sigma^2_{\ln w_2,t} \\
& + r \left(\beta_4 \cdot \frac{1}{w_{21,it}} + \beta_3 \cdot K_{it} - \beta_3 M_{cK} A_{cw_2} \cdot \frac{1}{c_{it}} \right) + \beta^{x_2}_{\sigma^2_{\ln c,it}} \cdot \sigma^2_{\ln c,it} \\
& + \beta^{x_2}_{\sigma^2_{\ln w_2,t}} \cdot \sigma^2_{\ln w_2,t} + \beta^{x_2}_{year} \cdot year_t
\end{aligned} \tag{48}
$$

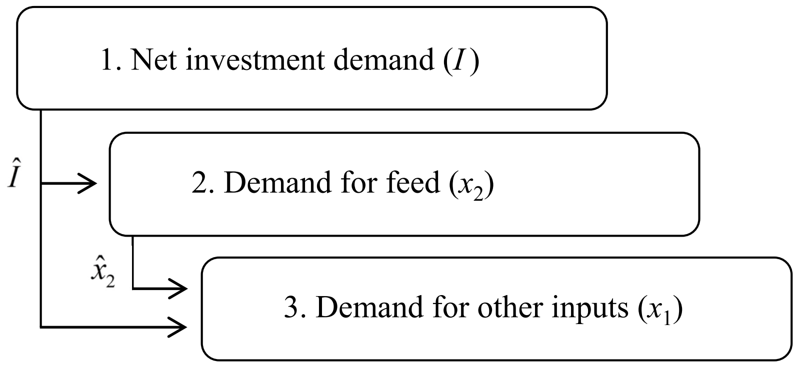
$$
\begin{aligned}
x_{1,it} = & \left[\exp\left(\omega_6 \cdot d_i^{edu} + \omega_7 \cdot age_{it} + \omega_8 \cdot inten_{it} + \omega_9 \cdot yield_{it} + \omega_{10} \cdot d_i^{south}\right)\right]^{-1} \cdot \\
& \left[r \cdot \left(\beta_5 + b_K \cdot K_{it} + A_{KK} \frac{1}{2} \cdot K_{it}^{\ 2} + A_{yK} \cdot \ln y_{it} K_{it} + \beta_2 \cdot w_{21,it} K_{it} + \beta_1 \cdot \ln c_{it} \right.\right. \\
& + \left(b_y + A_{w_2 y} \ln \lambda_{21}\right) \cdot \ln y_{it} + A_{yy} \frac{1}{2} \cdot \left(\ln y_{it}\right)^2 + A_{w_2 y} \cdot \ln y_{it} \ln w_{21,it} \\
& + A_{cc} \frac{1}{2} \cdot \left(\ln c_{it}\right)^2 + A_{cy} \cdot \ln y_{it} \ln c_{it} + \left(b_{w_2} + A_{w_2 w_2} \ln \lambda_{21}\right) \cdot \ln w_{21,it} \\
& \left. + A_{w_2 w_2} \frac{1}{2} \cdot \left(\ln w_{21,it}\right)^2 + A_{cw_2} \cdot \ln w_{21,it} \ln c_{it} \right) + \left(M_{cK} r - 1\right) \cdot c_{it} K_{it} \\
& - \frac{1}{\tau_{K,it}} \left(A_{yK} \cdot \ln y_{it} I_{it} + \beta_2 \cdot w_{21,it} I_{it} + M_{cK} \cdot c_{it} I_{it} + b_K \cdot I_{it} + A_{KK} \cdot K_{it} I_{it}\right) \\
& - M_{cK} \frac{1}{2} \cdot K_{it} c_{it} \sigma^2_{\ln c,it} - \beta_2 \frac{1}{2} \cdot K_{it} w_{21,it} \sigma^2_{\ln w_2,t} - A_{yy} \frac{1}{2} \cdot \sigma^2_{\ln y,i} \\
& \left. - A_{w_2 w_2} \frac{1}{2} \cdot \sigma^2_{\ln w_2,t} - A_{cc} \frac{1}{2} \cdot \sigma^2_{\ln c,it} \right] - \lambda_{21} \cdot w_{21,it} x_{2,it} + \beta^{x_1}_{year} \cdot year_t
\end{aligned}
\tag{49}
$$

where I_{it} denotes investment in the quasi-fixed factor and is the empirical equivalent to $\dot{K}$, $\beta_1 = b_c + A_{cw_2} \ln \lambda_{21}$, $\beta_2 = A_{w_2 K} \lambda_{21}$, $\beta_3 = \tau_x A_{w_2 K}$, $\beta_4 = A_{w_2 w_2} \tau_x \lambda_{21}^{-1}$ and $\beta_5 = a_0 + b_{w_2} \ln \lambda_{21} + A_{w_2 w_2} 1/2 \left(\ln \lambda_{21}\right)^2$. The time variable $year_t$ is added to account for technological change over the examined period (cf. Heshmati et al. 1995 or Cuesta 2000).

5.3 Estimation

The empirical model consisting of equations (47)–(49) forms a non-linear recursive system. It is recursive in net investment demand *I*—serving as an explanatory variable in the variable input demand equations. Furthermore, the system is recursive in variable input demand because the demand for purchased feed x_2 is an explanatory variable for the demand of other inputs x_1. The estimation structure is highlighted in Figure 25. The recursiveness allows the author to estimate first the net investment demand and second the variable input demand (x_2) in which the recovered value function parameters from the first step (M_{cK}, A_{cc}, A_{cw_2}, A_{cy} and β_1) are used. Third, the estimates for the numeraire input demand (x_1) equation are obtained in which the predictions from the first and second step ($\hat{I}$ and $\hat{x}_2$) appear as explanatory variables.

Figure 25. Estimation procedure



The factor demand equations are estimated by using the non-linear least square method. The estimator is the extension of the least squares estimation for linear models to nonlinear models and minimizes the sum of squared residuals (Cameron and Tridevi 2005). The estimation is carried out in Stata12 computer software using the estimation command "nl". Essentially, the non-linear least square method assumes that the error term variance is constant across observations; that is, homoscedastic (Verbeek 2000). However, this assumption is often found to be troubling in empirical studies for example due to missing explanatory variables and the consequence might be that the standard errors are incorrect and parameters might appear statistically significant (Urban and Mayerl 2006). To cope with this issue, the Huber-White standard errors based on an alternative estimate of the error term variance—implemented by the "vce(robust)" option in Stata12 computer software—are used here.

Non-linear least squares estimation itself does not take the heterogeneity among farms into account and this characteristic may lead to biased frontier and efficiency estimates (e.g., Abdulai and Tietje 2007). Following the Chamberlain approach firm-specific means of the explanatory variables can be considered in the demand equations to reduce the potential influence of unobserved heterogeneity effects on the estimates (Wooldridge 2010; Emvalomatis 2012). In this context, the approach requires inclusion of 7, 20 and 25 additional regressors in equation (47), (48) and (49), respectively. According to Emvalomatis (2012), to avoid an over-parameterized model and to reduce the possibly induced multicollinearity, only the farm-specific means of the constitutive terms—such as K, c, and w—are included. The discount rate r is assumed to be 0.05. For convergence reasons, allocative efficiency of variable factors λ_{21} is estimated as a scalar and initial parameters are chosen to ease convergence of the estimation.

6 Results for West German dairy farms

In this section, the empirical results for West German dairy farms are elaborated. First, the value function parameter estimates and the adjustment rate are analyzed (6.1). Second, differences in technical and allocative efficiency over time and by farm characteristics are explored (6.2). Third, the impact of uncertainty on factor allocation is interpreted and the effect of uncertainty on the efficiency measurement is elaborated (6.3). The results are used to evaluate how adjustment pressure, as for example induced by increases in input and milk price uncertainty is related to the optimal factor allocation. Fourth, the model and its results are critically reflected (6.4).

6.1 Value function parameter and adjustment rate

The goodness of fit measured in terms of the R^2 values for all equations—net investment, purchased feed and other input demand—shows with 0.496, 0.911 and 0.892 satisfying values. The full results with all parameter estimates can be found in Table 10 and Table 11. Table 6 provides estimates of the first- and second-order parameters of the value function (cf. equation (40)) which are retrieved from the estimated coefficients. Identifying the value function parameters is a challenging part and has only been possible through the specific structure of the empirical model (cf. section 5.2, equations (47)–(49))—e.g., the estimation of the aggregated β-parameters). 40% of the value function parameter estimates are significant at the 1% level. The estimates reveal that the value function is non-decreasing in output and input prices since the following conditions are met using the estimated parameters: $J_y^b \geq 0$, $J_{w_2}^b \geq 0$ and $J_c^b \geq 0$. The estimates further confirm that the conditions for the value function to be convex in the use of the quasi-fixed input are met: $J_{KK}^b > 0$. Conditions for concavity in input prices and non-increasing quasi-fixed input levels, however, are violated.[29]

[29] Concavity in input prices requires the Hessian matrix of J^b to be negative semi-definite, that is, all principal minors must be alternate in sign: $J_{w_2 w_2}^b < 0$, $J_{cc}^b < 0$ and $\left[J_{w_2 w_2}^b J_{cc}^b - \left(J_{w_2 c}^b \right)^2 \right] > 0$.

Table 6. First- and second-order value function parameters

Parameter	Estimate	p-value	Parameter	Estimate	p-value
a_0	7.50E+02	0.582	A_{w_2y}	1.84E+04	0.000***
b_K	1.45E+02	0.127	$A_{w_2w_2}$	5.17E+01	0.007***
b_{w_2}	1.94E+04	0.000***	A_{cy}	-1.14E+01	0.701
b_c	-3.57E+00	0.000***	A_{cw_2}	2.88E+00	0.710
b_y	3.78E+00	0.000***	A_{cc}	-5.30E+00	0.702
A_{KK}	1.51E+03	0.148	M_{cK}	1.23E-02	0.610
A_{yK}	-8.53E+01	0.881	A_{w_2K}	-4.87E+00	0.000***
A_{yy}	2.51E+02	0.045**			

Note: Asterisks ** and *** denotes statistical significance at the 5% and 1% level with standard errors based on either the delta-method or the standard variance estimator for least squares regression.
Source: Own calculations based on BMEL-Testbetriebsnetz, 1996–2010.

In a subsequent step, the structural parameters are used to retrieve the adjustment rate of the quasi-fixed factor $\left[r - M_{cK} - 1/2\,\sigma^2_{\ln c}\right]$ (cf. Epstein and Denny 1983), which amounts to 0.028 per year. This comparable low rate suggests that the dairy farms in the sample adjust sluggishly to their long-run equilibrium level of the quasi-fixed factor (livestock capital). This finding is in line with Chang and Stefanou (1988) or Howard and Shumway (1988) who report that the adjustment rate of the dairy cow stock in the U.S. is more lethargic compared to other durable long-term equipment according to a rather inelastic short-run milk supply. Also Rungsuriyawiboon and Hockmann (2012) find sluggish adjustment processes in capital and land for Polish farms. The observed sluggishness of capital adjustment can also be traced back to the existence of milk production quotas in the EU, which are suspected to hamper structural change (Piet et al. 2012).

6.2 Efficiency scores

A hypothesis test is performed to investigate whether farms in the sample operated (in)efficiently. For this, two different model specifications are compared: an unrestricted and a restricted model. In the unrestricted model it is assumed that the farms operate inefficiently and the inefficiency parameters are specified as time- and individual-specific (cf. equations (44)–(46)). In contrast, in the restricted model it is assumed that the farms operated perfectly efficient and the model is estimated by setting all (in)efficiency parameters in equations (47)–(49) equal to one. The test for the perfect efficiency hypothesis (cf. Rungsuriyawiboon and Hockmann 2012) is conducted using a likelihood ratio test with five, three and seven degrees of freedom,[30] respectively. Comparing the likelihood values of the restricted model and the unrestricted model, the test indicates that the null hypothesis of fully efficient farms is rejected. This means the unrestricted model specification is favored. In the following, the results are presented with respect to the average scores for the whole sample, for size groups, for regions and for agricultural education.

The mean of the technical and allocative efficiencies are reported in Table 7. Relative measures are used here, that is, to obtain the technical efficiency scores each efficiency-estimate is related to the respective farms' highest value: $\tau_{K,it}^{rel} = \tau_{K,it} / \tau_{K,i}^{\max}$, where $\tau_{K,\mathrm{i}}^{\max} = \max_t \left(\tau_{K,it} \right)$ and $\tau_{x,it}^{rel} = \tau_{x,it} / \tau_{x,i}^{\max}$, where $\tau_{x,\mathrm{i}}^{\max} = \max_t \left(\tau_{x,it} \right)$. For the allocative efficiency scores the procedure is differently and the farm-individual estimate is related to the highest sample value for each year: $\mu_{it}^{rel} = \mu_{it} / \mu_t^{\max}$, where $\mu_t^{\max} = \max_i \left(\mu_{it} \right)$. To investigate the presence of scale effects the mean efficiency scores are grouped by farm size categories, where farm size is measured in terms of average number of dairy cows. Three groups are used based on the terciles of the respective distribution: small (< 35 cows), medium (35–50 cows) and large farms (> 50 cows). Furthermore, the efficiency scores are grouped by location and agricultural education. Location is measured in terms of southern and northern farms. South refers to the federal states Baden-Württemberg, Bavaria, Rhineland-Palatinate, Hesse and Saarland. North refers to Lower Saxony, North Rhine-Westphalia and Schleswig-Holstein. Agricultural education is categorized as low—farm manager has not obtained higher agricultural education e.g., completed vocational training—and high—farm manager has obtained higher agricultural education e.g., master craftsman diploma and university/applied university degree.

[30] This results from the assumption that the farms operated perfectly efficient; hence, a different number of explanatory variables cancels out in the net investment demand, feed demand and other input demand equation.

Table 7. Estimated average efficiency scores

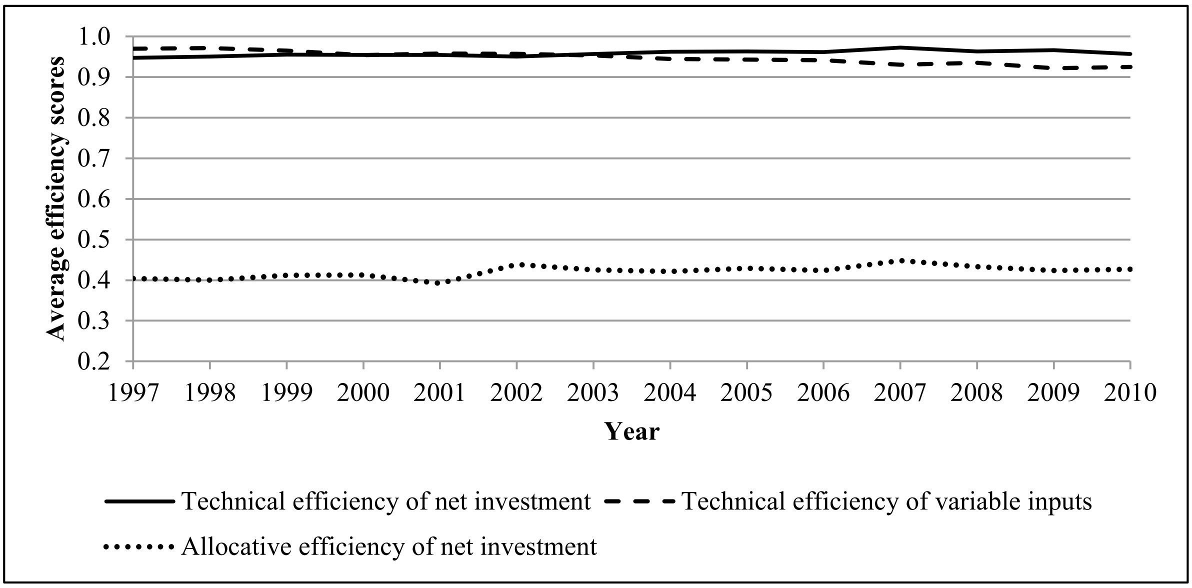
Category	Level	Technical efficiency		Allocative efficiency
		net investment $1/\tau_{K,it}^{rel}$	variable factors $1/\tau_{x,it}^{rel}$	net investment μ_{it}^{rel}
Mean	--	0.959	0.948	0.420
Herd size [# of cows]	< 35	0.962[a,b]	0.950	0.415[b]
	35–50	0.956	0.946	0.411[c]
	> 50	0.957	0.949	0.434
Location	North	0.962[d]	0.955[d]	0.410
	South	0.957	0.946	0.424
Agricultural education	Low	0.959	0.950[d]	0.410
	High	0.957	0.944	0.447

Note: Significance of differences between efficiency scores by group are denoted as follows: [a] significant between small and medium farms; [b] significant between small and large farms; [c] significant between medium and large farms; and [d] significant between the groups of location and education, respectively.
Source: Own calculations based on BMEL-Testbetriebsnetz, 1996–2010.

The technical efficiency score of net investment ($1/\tau_{K,it}^{rel}$) is on average 0.959 (cf. Table 7) and varies between 0.678 and 1.0. The scores remain nearly constant over time (cf. Figure 26). The mean technical efficiency score of variable inputs ($1/\tau_{x,it}^{rel}$) amounts to 0.948 ranging from 0.632 and 1.0. Here a slight decrease of average efficiency can be observed over time: from 0.970 to 0.925 between 1997 and 2010 (cf. Figure 26). The estimated μ_{it} amounts to 0.28 on average and all values are below 1, hence, it can be concluded that all farms overuse their dairy cow stock with regards to observed prices (quasi-fixed). In a subsequent step the relative efficiency scores for the quasi-fixed factor (μ_{it}^{rel}) are obtained and the mean of μ_{it}^{rel} amounts to 0.420 indicating that the shadow marginal value of the capital stock is less than the actual marginal value of the capital stock, on average. Interestingly, the allocative efficiency is more pronounced compared to the technically one.

The values for technical efficiency are comparable to previous studies on the efficiency of German dairy farms—e.g., Abdulai and Tietje (2007), Brümmer et al. (2002), Sauer and Latacz-Lohmann (2014)—and to international dynamic efficiency studies on dairy farms—e.g., Serra et al. (2011) and Emvalomatis et al. (2011). Serra et al. (2011) and Emvalomatis et al. (2011) report values of 0.896 and 0.782, respectively. Emvalomatis et al. (2011) analyze German dairy farms but their approach does not distinguish between technical efficiency of net investment and variable factors.

Figure 26. Efficiency scores traced over time



Source: Own calculations based on BMEL-Testbetriebsnetz, 1996–2010.

Allocative efficiency for variable inputs λ_{21}—measured in terms of a price distortion of feed relative to other inputs—is a scalar and shows an estimate of 2.69 implying that the shadow price ratio of feed relative to other inputs is higher than the observable price ratio. It may be conjectured that purchased feed compared to other inputs is underused. The relevant efficiency literature offers mixed results here: Reinhard and Thijssen (2000) found that feed and nitrogen fertilizer is overused compared with intermediate inputs for Dutch dairy farms. For Italian dairy farms, Maietta (2000) found an underuse of forage crops and purchased feed compared to hired labor. Serra et al. (2011) report values for allocative inefficiency of 0.018 for Dutch dairy farms using a directional distance function. However, these authors do not distinguish between allocative efficiency of quasi-fixed or net investment and allocative efficiency of variable inputs. Emvalomatis et al. (2011) report technical efficiency scores for Dutch and German dairy farms, however, these authors do not estimate allocative efficiency scores.

Table 7 indicates that the technical efficiency scores of net investment slightly decrease with farm size, significantly between the small (< 35 cows) and the medium (35–50 cows) as well as between the small and the large farms (> 50 cows). Significance is based on a group-comparison test and the p-values are presented in Table 8. For the variable factors' technical efficiency however, size differences cannot be confirmed. Contrasting to these findings, positive scale effects are often discussed in the literature; however, the distinction between quasi-fixed and variable factor use is often lacking. A positive relationship of size and technical efficiency (variable factors) for dairy farms is found by Hadley (2006) for the United Kingdom, Alvarez and Arias (2004) for Spain, Kumbhakar et al. (1991) for the U.S. and Sauer and Latacz-Lohmann (2014) for Germany. Mosheim and Lovell (2009) report increasing technical (and allocative) efficiency scores for U.S. dairy farms with small (< 30 cows) and very large (> 2,000 cows) herd sizes. Allocative efficiency of German dairy farms significantly differs between small and large farms where larger farms show higher values; the medium farms show the lowest efficiency. In other words, the large as well as the small operate comparably efficient regarding the dairy stock, allocatively and technically. This result provides an explanation of the phenomenon that large farms grow and small persist resulting in a disappearing middle size class (e.g., Weiss 1999).

The results presented in Table 7 and Table 8 further indicate that farms in the North of Germany—25.2% of the observations—exhibit a higher value of technical efficiency of net investment and of variable inputs than farms in the South, and the difference is statistically significant at the 1% level. One reason might be that northern farms use a more intensive production system—e.g., use more purchased feed per cow—and, hence, show a higher level of technical efficiency than extensive farms (e.g., Alvarez and del Corral 2010). Southern farms exhibit higher average allocative efficiency compared to northern farms, although not statistically significant. A comparison of the North-South difference with former efficiency studies for dairy farms in Germany is difficult. Brümmer and Loy (2000) and Brümmer et al. (2002) analyze farms located in Schleswig-Holstein (northern Germany) and found average technical efficiency of 0.96 and 0.95, respectively. Kellermann et al. (2011) report an average technical efficiency of 0.88 for dairy farms in Bavaria and Lakner (2009) found that farms in western and northern Germany are more efficient than farms in southern and eastern Germany. Also Sauer and Latacz-Lohmann (2014) analyze German dairy farms in all federal state (except city-states) and found that farms located in northern Germany produce more efficiently and gain higher efficiency increases due to innovations. The only academic dynamic efficiency study for German dairy farms conducted by Emvalomatis et al. (2011) does not provide efficiency results for different German federal states or regions.

Farms managed by persons with a higher agricultural education—33.9% of the observations are master craftsman and graduates—show a higher allocative efficiency of net investment, although not statistically significant (Table 7 and Table 8). In contrast, higher educated farmers show slightly lower values of technical efficiency. The differences among the groups are only statistically significant at the 1% level for technical efficiency of variable factors. This indicates that higher agricultural education compared to lower education results in similar efficiency scores of the sample farms. One explanation could be that the majority of farmers—66.1% of the observations—have gone through the German apprenticeship system. This provides practical, technical and economic knowledge over three years in courses on and off the job. Whereas training of those in the higher education category—e.g., graduates—is mainly theoretically based. In comparison, Stefanou and Saxena (1988) estimate allocative efficiency of variable inputs and show that education and experience are substitutes and education increases allocative efficiency because higher educated farmers have a higher ability to learn. The studies investigating the relationship between education and technical efficiency in agriculture, however, obtain mixed results. Kumbhakar et al. (1991) found a positive effect of education (represented by the categories: schooling up to high school, above high school and college). Abdulai and Tietje (2007) report that agricultural education of dairy farmers is positively related to technical efficiency and Sauer and Latacz-Lohmann (2014) show that farmers with a university/applied university degree show higher efficiency scores. In contrast, no significant effect of education on efficiency has been found by Tauer (1993) for New York dairy farms and Bravo-Ureta and Rieger (1991) for New England dairy farms (education is represented by number of years of schooling completed by the farm manager).

Table 8. P-values of the group comparison test

Group comparison test	p-values for differences		
	technical efficiency		*allocative efficiency*
	net investment $1/\tau^{rel}_{K,it}$	variable factors $1/\tau^{rel}_{x,it}$	net investment μ^{rel}_{it}
by herd size			
Small – Medium	0.001***	0.222	1.000
Small – Large	0.016**	1.000	0.009***
Medium – Large	1.000	0.519	0.001***
by location			
North – South	0.005***	0.000***	0.990
by education			
Low – High	0.185	0.000***	1.000

Note: Asterisks ** and *** denote statistical significance at the 5% and 1% levels based on one-way ANOVA.

6.3 Efficiency and uncertainty

Exploring the role of uncertainty on optimal factor allocation, the results show that the demand for feed is negatively related to the variance of the feed concentrate price and investment is negatively related to the variance of the milk price (cf. Table 10 and Table 11). A negative investment-uncertainty relationship has been empirically confirmed, for instance by Pietola and Myers (2000), Boetel et al. (2007) or Hinrichs et al. (2008). However, Koetse et al. (2006) have performed a meta-regression on 39 studies that investigate investment under uncertainty and the results show that 64% of the analyzed studies found a negative relationship whereas 36% found a positive relationship of investment and uncertainty.

The variance variable $\sigma^2_{\ln c,it}$ enters the net investment demand equation within the interaction term ($\sigma^2_{\ln c,it} K_{it}$). According to the concept of simple slopes three different levels of livestock capital are distinguished to estimate a slope coefficient for each level capturing the impact of uncertainty: first, the mean herd size with one standard deviation measure below the mean (26 cows); second, the mean herd size (44 cows); and third, the mean plus one standard deviation (62 cows). The results as presented in Table 9 reveal a persistent negative effect of uncertainty on the net investment demand over all the size categories. The impact increases with size and shows the highest value for the large farms (mean size of 62 cows).

Table 9. Impact of uncertainty on farm investment by herd size

Herd size	"simple slope"	p-value
Mean *minus* standard deviation: 26 cows	-0.396	0.0010***
Mean: 44 cows	-0.544	0.0000***
Mean *plus* standard deviation: 62 cows	-0.692	0.0004***

Note: Asterisks *** denotes statistical significance at the 1% level with standard errors by Jaccard and Turrisi (2003).
Source: Own calculations based on BMEL-Testbetriebsnetz, 1996–2010.

To underline the importance of the impact of price uncertainty on the factor demand and efficiency (measurement), the estimates of two net investment demand equations are compared: one with uncertainty variables (a), and one without (b). The results of both models are presented in Table 10 and Table 11. On the left-hand side the full results are presented. On the right-hand side, the results of the model comparison with and without uncertainty variables being the base for the likelihood ratio test are presented. To carry out this test the robust version of the standard errors cannot be use; accordingly, the p-values between the full results and the model version

(a) slightly differ. Furthermore, to conduct the likelihood ratio test for a model comparison (right-hand side of Table 10 and Table 11), an equal number of observations is necessary. This is fulfilled for the net investment and feed demand equation but not for the other input demand because the number of obtained positive predictions of the feed demand equation—entering the other input demand equation as explanatory variable—differs between the model versions (a) and (b). To achieve an equal number of observations, the prediction of the feed demand equation based on model version (b) is used in the other demand equation. According to that, the results of model version (a) slightly differ from the original results as shown on the right-hand side of Table 11.

Table 10. Full results for net investment and feed demand

				Model comparison		
				(a) with uncertainty	(b) without uncertainty	
	Coefficient	Estimate	p-value[a]	p-value[b]	Estimate	p-value[b]
Net investment demand	ω_1	-1.86E-02	0.918	0.908	1.07E-02	0.958
	ω_2	-2.26E-03	0.719	0.730	-8.34E-04	0.918
	ω_3	-2.34E-01	0.215	0.271	-4.11E-01	0.119
	ω_4	5.43E-02	0.359	0.436	1.21E-01	0.166
	ω_5	-3.18E-01	0.264	0.164	-1.61E-01	0.526
	β_1	-7.10E-01	0.904	0.919	9.94E+00	0.925
	M_{cK}	1.23E-02	0.610	0.637	3.95E-03	0.915
	A_{cy}	-1.14E+01	0.701	0.731	-5.16E+01	0.922
	A_{cc}	-5.30E+00	0.702	0.736	-3.85E+01	0.921
	A_{cw_2}	2.88E+00	0.710	0.749	1.88E+01	0.922
	$\beta^I_{\sigma^2_{\ln c,it}K_{it}}$	-3.71E-01	0.145	0.164	--	--
	$\beta^I_{\sigma^2_{\ln c,it}}$	-5.44E-01	0.000***	0.000***	--	--
	β^I_{year}	1.91E-04	0.000***	0.000***	1.82E-04	0.000***
Feed demand	ω_{11}	5.29E-02	0.842	0.846	-6.26E+00	0.000***
	ω_{12}	-8.97E-04	0.931	0.932	5.15E-02	0.098*
	ω_{13}	-1.34E+00	0.000***	0.000***	3.95E+00	0.002***
	β_2	-1.31E+01	0.121	0.076*	2.14E+01	0.008***
	β_3	1.47E+01	0.026**	0.002***	1.35E+03	0.000***
	β_4	2.65E+02	0.000***	0.000***	2.42E+02	0.000***
	b_K	1.45E+02	0.127	0.147	-1.25E+01	0.799
	A_{KK}	1.51E+03	0.148	0.179	-1.58E+02	0.776
	A_{yK}	-8.53E+01	0.881	0.904	1.68E+02	0.714
	$\beta^{x_2}_{\sigma^2_{\ln c,it}}$	3.44E+02	0.000***	0.000***	--	--
	$\beta^{x_2}_{\sigma^2_{\ln w_2,t}}$	-8.57E+00	0.239	0.172	--	--
	$\beta^{x_2}_{year}$	-2.73E-01	0.000***	0.000***	-1.90E-01	0.000***

Note: Asterisks *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Superscript [a] denotes robust Huber-White standard errors, while [b] denotes the respective non-robust versions.

Table 11. Full results for the other input demand

				Model comparison			
				(a) with uncertainty		(b) without uncertainty	
	Coefficient	Estimate	p-value[a]	Estimate	p-value[b]	Estimate	p-value[b]
Other input demand	ω_6	-5.88E-02	0.022**	-5.81E-02	0.000***	-3.60E-02	0.000***
	ω_7	-6.22E-03	0.000***	-6.21E-03	0.000***	-5.59E-03	0.000***
	ω_8	3.16E-01	0.000***	3.18E-01	0.000***	2.76E-01	0.000***
	ω_9	-3.11E-02	0.007***	-2.88E-02	0.000***	-1.13E-03	0.800
	ω_{10}	5.49E-02	0.060*	5.33E-02	0.000***	5.23E-02	0.000***
	β_5	1.03E+03	0.000***	1.04E+03	0.000***	8.08E+02	0.000***
	$A_{w_2 y}$	1.84E+04	0.000***	1.90E+04	0.000***	2.34E+04	0.000***
	$\ln(\lambda_{21})$	9.92E-01	0.000***	9.88E-01	0.000***	8.67E-01	0.000***
	A_{yy}	2.51E+02	0.045**	2.28E+02	0.230	1.68E+04	0.000***
	$A_{w_2 w_2}$	5.17E+01	0.007***	5.54E+01	0.001***	1.36E+04	0.000***
	b_{w_2}	1.94E+04	0.000***	1.97E+04	0.000***	1.22E+04	0.000***
	b_c	3.57E+00	0.000***	-3.55E+00	0.000***	-6.36E+00	0.000***
	b_y	3.78E+00	0.000***	3.80E+00	0.000***	3.31E+00	0.000***
	$\beta_{year}^{x_1}$	1.49E+02	0.045**	1.46E+00	0.000***	2.16E-01	0.245

Note: Asterisks *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Superscript [a] denotes robust Huber-White standard errors, while [b] denotes the respective non-robust versions.

The estimated coefficients differ in their absolute values, though not remarkably in their significance levels; however, the uncertainty model (a) is characterized by comparatively lower standard errors. These findings indicate a considerable omitted variables bias, which results from not taking uncertainty into account. Moreover, a likelihood ratio test is conducted which reveals at the 1% level that the model with uncertainty has a statistically significant better performance; that is, the null hypothesis of no uncertainty is rejected. In addition to the better model performance from an econometric perspective, the implications of the omitted variables bias are more severe in this context. Comparing the mean technical efficiency of net investment of both models shows a significantly higher score if factor price uncertainty is considered: 0.959 versus 0.919. That is, not accounting for the impact of price uncertainty will lead to the conclusion that firms are less efficient even though this is not the case. Thus, farms appear seemingly technically inefficient. A comparable result has been obtained by Skevas et al. (2012)

who show that ignoring production uncertainty leads to an overestimation of farmers' technical inefficiency scores. Likewise, the data used in this thesis reveal that the same is true for allocative efficiency: German dairy farms are seemingly allocatively inefficient, that is, the allocative efficiency scores are lower if uncertainty is disregarded.

6.4 Critical reflection

In the empirical implementation, one quasi-fixed input (livestock capital) and two variable inputs (purchased feed and other inputs) are used to operationalize the complex theoretical model. The results may vary if a different number of quasi-fixed inputs such as land and milk quota is used. The extension of the applied dynamic efficiency model under uncertainty to multiple quasi-fixed inputs is possible; however, it will considerably increase the model's complexity. Recently, Rungsuriyawiboon and Hockmann (2012) have extended the dynamic efficiency model of Rungsuriyawiboon and Stefanou (2007) to capture multiple quasi-fixed inputs assumed to be independent in the econometric model. This imposes that matrices of the value function reduce to diagonal matrices, e.g., the off-diagonal elements are equal to zero to ease the derivation and the empirical setup. However, these authors do not account for price uncertainty. A direct comparison of the results of the two papers is not possible because these studies analyze different sectors (polish farms and U.S. electricity companies). In addition, further disaggregated variable inputs could provide further insights and the treatment of adjustment costs could be refined. In this model, adjustment costs are expressed by a simple adjustment rate to be used in the linear accelerator model. More sophisticated adjustment cost functions, which have been suggested by e.g., Hamermesh and Pfann (1996), may lead to asymmetric adjustments of the capital stock and increased investment reluctance which, in turn, have an impact on the long-run efficiency measurement.

The importance of the underlying assumptions and the chosen estimation approach for the obtained efficiency levels has been pointed out in the current efficiency literature. By analyzing 89 Spanish dairy farms, Orea et al. (2004) stress that the estimation results may differ depending on how inefficiency has entered the data generating process: different assumptions, as for example input-oriented or output-oriented measures of efficiency, may yield different estimates. These authors further state that the input-oriented model is superior to the output-oriented model for Spanish dairy farms and the differences are reflected in the efficiency scores: choosing an output-oriented model would underestimate efficiency which, in turn, may influence policy recommendations. Hallam and Machado (1996) estimate efficiency scores for

Portuguese dairy farms and found considerably different efficiency scores depending on the chosen estimation procedure.

The structure and the estimation of the factor demand equations highlights another challenge namely the consistent estimation of the value function parameters and efficiency scores. The equations are highly non-linear and the parameters appear in different equations and hence this linkage between the equations has to be considered in the estimation procedure. Furthermore, the specification of the efficiency scores as time- and individual specific was possible for three-out-of-four efficiency scores: technical and allocative efficiency of net investment and technical efficiency of the variable factors. Given the structure of the theoretical model the fourth inefficiency parameter—allocative efficiency of the variable factors—is estimated as a scalar. Nevertheless, this allows the researcher to investigate whether an over- or underuse of variable factors exists. Moreover, the factor demand equations depend on factor combinations that are predetermined by the theoretical model and its derivation process. Other factors might also impact the factor demand function; Brümmer and Loy (2000) highlighted that investment decisions in the dairy sector are influenced for example by technological innovations. However, the dynamic efficiency model under uncertainty results in stochastic factor demand functions that are consistent with the firms' optimization behavior.

7 Summary and conclusion

This thesis examines the dynamic efficiency of West German dairy farms and the effect of uncertainty in the optimal factor allocation process. Thus far uncertainty has been ignored when deriving dynamic efficiency measures; this also prevented the identification of technical efficiency measures for net investment. The application of a model enhanced by Hüttel et al. (2011)—which combines investment under uncertainty with (deterministic) dynamic efficiency analysis using a static shadow cost approach and a stochastic dynamic dual model of investment—contributes to filling this gap. The model extends existing models of dynamic efficiency by explicitly allowing for stochasticity in prices and outputs. As a result, the volatility of factor prices and outputs enter the demand functions for variable and quasi-fixed production factors as the basis for estimating efficiency. Thus, uncertainty not only affects firms' optimal adjustment of production factors but also the quantification of their economic performance. From an econometric perspective, disregarding uncertainty may lead to an omitted variable bias in the estimation of efficiency scores.

The dynamic efficiency model is applied to West German dairy farm-level data from the national German farm accountancy data network covering the years 1996 to 2010 to study the effect of uncertainty in the optimal factor allocation process. The results state that West German dairy farms operate at high levels of technical efficiency. The findings further show that livestock capital is overused for observed prices for variable and quasi-fixed factors, but at a decreasing rate with increasing farm size. The average allocative efficiency of net investment and the allocative efficiency of the variable factors (purchased feed) in relation to the numeraire factor (other inputs) indicate a suboptimal use of both net investment and purchased feed.

With regard to the question of how changes in the policy environment impact the optimal factor allocation of farms, the results show the following. Considering uncertainty is crucial for deriving dynamic efficiency measures: neglecting uncertainty within the estimation procedure will overestimate the average inefficiency score. Thus, farms appear seemingly inefficient. Furthermore, positive scale effects are often discussed in the literature and accordingly growth is recommended as a future strategy for farms—particularly dairy farms. However, the influence of uncertainty and a distinction between quasi-fixed and variable factor use is often lacking. In contrast, the results reveal a significant interaction between price uncertainty and livestock capital by size: uncertainty has a negative impact on farm-level investments in herd size that increases with farm size. The demand for feed is negatively related to the variance of the feed concentrate price.

These findings are not only interesting from an academic perspective; they have further implications for analyzing the relative performance of specific farm types like cash crops or other livestock farms. Due to external and internal conditions such as the socio-economic environment or farmer characteristics, the degree of uncertainty may vary among farm types. As a consequence, the impact of uncertainty on efficiency level estimates may differ as well. Hence, an adequate measurement of dynamic efficiency is important for obtaining meaningful results with regard to the evaluation of the relative farm-type performance. This is not only relevant for the agricultural sector, but applies to firms and industries that operate in highly-volatile markets.

Several directions for further research are possible. With the end of the milk quota regime in 2014/2015 a profit maximization approach might be an alternative approach to the cost minimization perspective (e.g., Ang and Oude Lansink 2014). Accordingly, a dynamic dual efficiency model under uncertainty could start from a profit maximization problem. Furthermore, incorporating technical change seems to be an important issue, particularly for dairy farms in Europe, as shown by Sauer and Latacz-Lohmann (2014). Another crucial aspect is animal welfare research, which has gained considerable attention in recent years: animal welfare may affect technical efficiency but may also affect economic (dynamic) efficiency. In this regard, the usage of pasture for grazing dairy cows is a highly debated topic. Grazing is associated with animal welfare (Ellis et al. 2009) but efficiency studies that aim to reveal an economic (efficiency) effect are scarce. Indeed, few efficiency studies consider veterinary expenses in the definition of production costs or incorporate pasture usage as an efficiency determinant (e.g., Alvarez and del Corral 2010; Lakner et al. 2011; Pierani and Rizzi 2003; Sauer and Latacz-Lohmann 2014). Attempts were made by Barnes et al. (2011) to explicitly incorporate animal welfare—e.g., average lameness—into static DEA and this could be extended to dynamic DEA, or the dynamic efficiency model presented in this thesis could be extended such that it captures animal welfare and the effect of grazing in the estimation procedure and still offers the possibility to consider price uncertainty. Furthermore, with improved data that go beyond accounting data and improved estimation models, our understanding of the relation among farm-, environmental- and animal-specific characteristics and efficiency could be enhanced.

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Appendices

Appendix A. Selected empirical studies of technical efficiency in dairy farming

Table 12. Technical efficiency studies in dairy farming

Author(s)	Year	Country	Period	Farms
Abdulai and Tietje	2007	DE	1997–2005	149
Alvarez and Arias	2004	ES	1993–1998	196
Alvarez et al.	2006	ES	1993–1998	71
Alvarez and del Corral	2010	ES	1999–2006	130
Bravo-Ureta and Rieger	1991	U.S.	1984	511
Brümmer et al.	2002	DE	1991–94	44
Cuesta	2000	ES	1987–1991	82
Emvalomatis et al.	2011	DE	1995–2005	1,439
Hallam and Machado	1996	PT	1989–1992	85
Kumbhakar	1993	U.S.	1985	89
Kumbhakar et al.	1989	U.S.	1985	89
Kumbhakar et al.	1991	U.S.	1985	519
Kumbhakar and Heshmati	1995	SE	1976–1988	1,425
Kovacs and Emvalomatis	2011	DE, HU, NL	2001–2005	982, 23, 178
Maietta	2000	IT	1980–1992	41
Maietta	2002	IT	1980–1992	41
Mosheim and Lovell	2009	U.S.	2000	619
Orea et al.	2004	ES	1987–1991	89
Pierani and Rizzi	2003	IT	1980–1992	41
Reinhard and Thijssen	2000	NL	1985–1995	434
Sauer and Latacz-Lohmann	2014	DE	1995–2010	2,697
Serra et al.	2011	NL	1995–2005	639
Silva and Stefanou	2003, 2007	U.S.	1986–1992	60
Stefanou and Saxena	1988	U.S.	1982	131
Tauer	1993	U.S.	1990	395

Note: The countries are abbreviated according to ISO 3166-2: AR: Argentina, CL: Chile, DE: Germany, ES: Spain, HU: Hungary, IT: Italy, NL: Netherlands, PT: Portugal, SE: Sweden, U.S.: United States of America and UY: Uruguay.
Source: Based on Bravo-Ureta et al. (2007).

Appendix B. Additional information on the data

Table 13. Prices for cull cows at the federal state level in Germany

Year	BW	BY	HE	NI	NW	RP	SL	SH
1997	1.61	1.66	1.61	1.65	1.64	1.61	1.61	1.52
1998	1.99	2.00	1.98	2.00	1.98	1.98	1.98	1.94
1999	1.90	1.87	1.81	1.84	1.84	1.81	1.81	1.85
2000	2.03	2.00	1.92	2.03	1.99	1.92	1.92	2.02
2001	1.54	1.65	1.58	1.62	1.61	1.54	1.61	1.39
2002	1.65	1.61	1.54	1.61	1.58	1.54	1.54	1.62
2003	1.75	1.69	1.65	1.72	1.69	1.65	1.65	1.70
2004	1.88	1.83	1.79	1.86	1.85	1.79	1.79	1.84
2005	2.21	2.16	2.13	2.22	2.21	2.13	2.13	2.21
2006	2.34	2.28	2.27	2.34	2.33	2.27	2.27	2.36
2007	2.30	2.26	2.23	2.31	2.30	2.23	2.23	2.33
2008	2.56	2.52	2.49	2.56	2.55	2.49	2.49	2.57
2009	2.26	2.22	2.22	2.28	2.27	2.22	2.22	2.27
2010	2.32	2.27	2.25	2.32	2.31	2.25	2.25	2.32

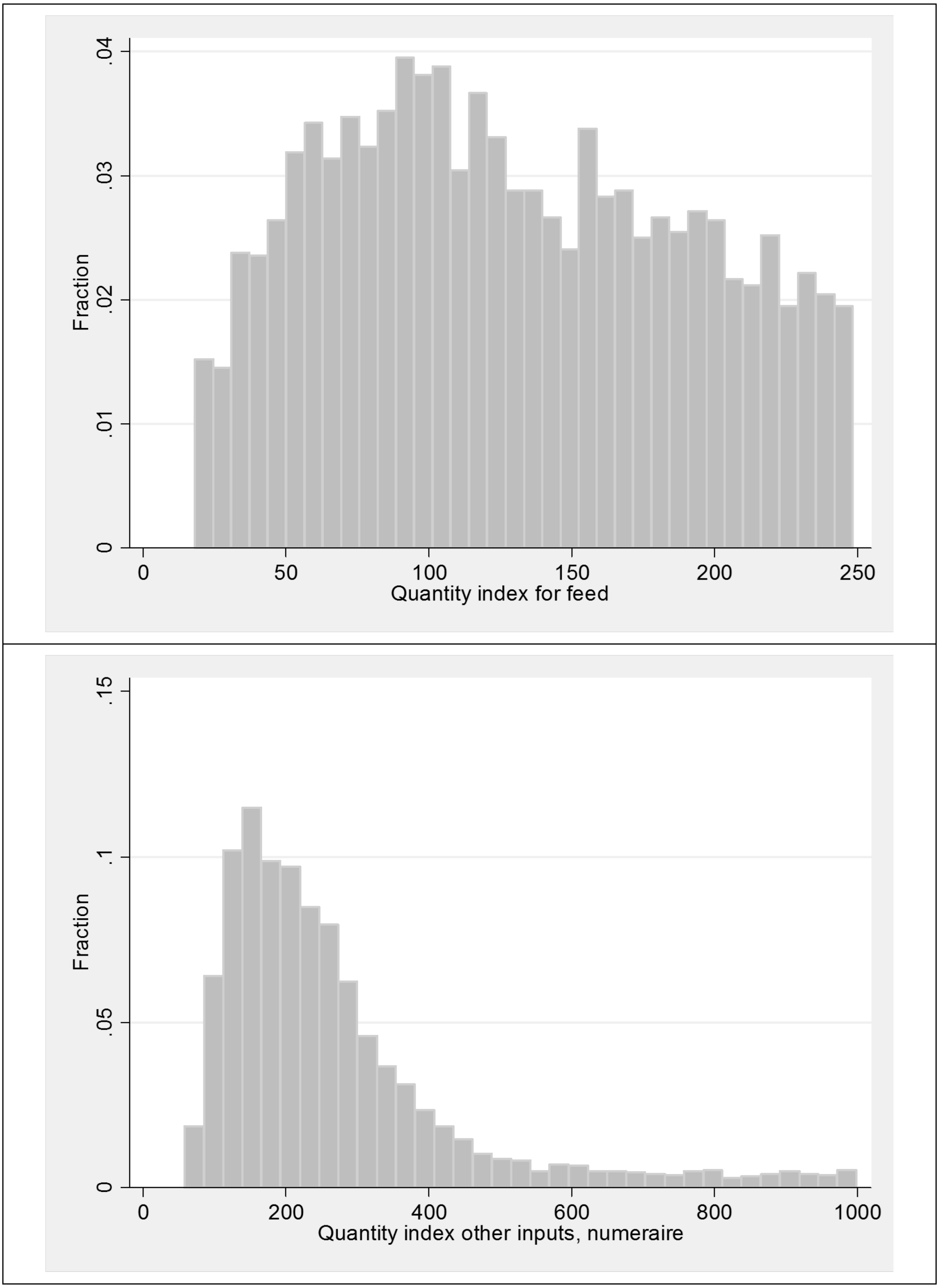
Note: The federal states are abbreviated according to ISO 3166-2: BW: Baden-Württemberg, BY: Bavaria, HE: Hesse, NI: Lower Saxony, NW: North Rhine-Westphalia, RP: Rhineland-Palatinate, SL: Saarland and SH: Schleswig-Holstein. Prices are in Euros per kg.
Source: AMI (diverse volumes).

Table 14. Average yearly deposit rate of interest in Germany

Year	Deposit rate of interest h_t [%]	Year	Deposit rate of interest h_t [%]
1997	4.29	2004	3.03
1998	4.04	2005	2.82
1999	3.54	2006	2.66
2000	4.76	2007	2.56
2001	4.12	2008	2.48
2002	3.77	2009	2.43
2003	3.26	2010	2.42

Source: Deutsche Bundesbank.

Figure 27. Histogram of feed and other inputs demand



Note: The cutoff level of the other inputs quantity index is set to 1000 to improve the readability.
Source: Own calculations based on BMEL-Testbetriebsnetz, 1996–2010.